Industry 6.0

Technology, Practices, Challenges, and Applications

Edited by
C KISHOR KUMAR REDDY, SRINATH DOSS, LAVANYA PAMULAPARTY, KARI LIPPERT, and RUCHI DOSHI

FUTURE GENERATION INFORMATION SYSTEMS

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Industry 6.0

What are the means to create a paradigm shift from conventional to intelligent companies? *Industry 6.0: Technology, Practices, Challenges and Applications* shows how integrating Industry 6.0 technology with data creates a framework for that shift. The book discusses the limitations, pitfalls, and open research questions in Industry 6.0, as well as the most recent advances, architectures, frameworks, applications, and novel practices, methods, and techniques. These are vital for resolving intelligent Internet of Things issues. There is a special focus on sustainable growth, humanization and environmentally friendly intelligent system applications, and an emphasis on the latest innovations in intelligent systems in classical machine learning, deep learning, Internet of Things (IoT), Industrial Internet of Things (IIoT), blockchain, knowledge representation, knowledge management, big data, and natural language processing (NLP).

Features:

- Presents the latest trends in the fields of intelligent systems, machine intelligence, deep learning, and Industrial Internet of Things for smart environments.
- Discusses securing the mobile ad hoc network (MANET) by detecting the Intrusions using CSO and XGBoost model.
- Highlights the methods of smart things in collaborative autonomous fleets and platforms for integrating applications across different business and industry domains.
- Focuses on intelligent process manufacturing, automation using robotics, development of robotic appliances, and smart manufacturing.
- Covers data-driven agriculture, crop disease prediction, drip irrigation systems, pesticide and fertilizer sprinkling using the Industrial Internet of Things, and water estimation systems.

With many contemporary articles from both scientists and practitioners working in many fields where intelligent systems and the IIoT can break new ground, the text is assembled to aim at a readership that includes researchers, statisticians, practitioners, scientists, and developers.

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With the evolution of future generation computing systems, it becomes necessary to occasionally take stock, analyze the development of its core theoretical ideas, and adapt to radical innovations. This series will provide a platform to reflect the theoretical progress, and forge emerging theoretical avenues for the future generation information systems. The theoretical progress in the Information Systems field (IS) and the development of associated next generation theories is the need of the hour. This is because Information Technology (IT) has become increasingly infused, interconnected and intelligent in almost all context.

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Contents

Preface

Industry 6.0 represents the next phase in the evolution of industrial manufacturing and automation. It builds upon the concepts of Industry 5.0 but takes them to a more advanced and interconnected level. In the era of Industry 5.0, the industrial landscape is undergoing a profound transformation driven by advanced technologies and data-driven decision-making. A smart environment in Industry 6.0 represents the pinnacle of this evolution, encompassing cutting-edge solutions that optimize industrial operations, enhance sustainability, and improve overall competitiveness.

The primary aim of this book is to achieve a paradigm shift in industrial operations. It seeks to enhance efficiency, productivity, and sustainability while simultaneously addressing challenges such as resource optimization, risk management, and adaptability to dynamic market conditions. By harnessing the power of advanced technologies, a smart environment in Industry 6.0 aims to empower decision-makers with real-time insights, enable data-driven decision-making, and drive innovations that lead to a more competitive and resilient industrial landscape.

The scope of the proposed book is extensive, encompassing a wide range of applications and technologies. From smart homes that automate household tasks and optimize energy usage to smart cities that use data and connectivity to enhance urban living, the concept of smart environments extends to industries, agriculture, manufacturing, healthcare, transportation, education, and beyond. It encompasses the development of intelligent buildings, responsive infrastructure, and interconnected ecosystems. It includes the deployment of IoT devices and sensors for real-time data collection, the development of sophisticated digital twins to model and optimize physical assets and processes, and the use of artificial intelligence, machine learning and deep learning to drive predictive analytics and autonomous decision-making. Furthermore, it extends beyond the boundaries of individual industrial facilities, integrating entire supply chains and fostering collaboration among diverse stakeholders.

About the editors

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Chapter 1

Exploring the synergy of IIoT, AI, and data analytics in Industry 6.0

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1.1 INTRODUCTION TO INDUSTRY 6.0: TECHNOLOGICAL PARADIGM SHIFTS AND EVOLUTION

Industry 6.0 is more than just upgrading factories – it's about revolutionizing entire industries by bringing in advanced technologies. These technologies work together to make informed decisions, increase productivity, and offer unparalleled customization. It's the next big step in industrialization, focusing on creating smart manufacturing systems that need minimal human involvement. India, with its growing economy, robust technology infrastructure, and talented workforce, is in a great position to be a significant player in the Industry 6.0 scene [1].

In Industry 6.0, we're blending human knowledge with artificial intelligence, using cloud computing, harnessing energy efficiently, getting humans and robots to work together, and making sense of big data [2]. There's also the emerging field of quantum computing, which adds another layer of complexity and capability.

Looking ahead, we're in the midst of a rapid technological shift that's changing how we live and work. Predictions suggest that by 2050, technology could achieve full autonomy. While it's hard to predict exactly how this revolution will unfold, one thing is clear – it's going to be an interdisciplinary world where everyone globally has a role to play in shaping the future.

1.1.1 Key differences and unique characteristics of each industrial revolution

The dawn of the Industrial Revolution, known as Industry 1.0, emerged in the late 18th century. This era marked a significant shift as mechanized production methods began to reshape economies and societies worldwide, powered by coal and steam. It marked the birth of factories and the era of bulk production. The second industrial revolution (Industry 2.0), as shown in Figure 1.1, characterized by electricity and the assembly line, increased efficiency and gave rise to industries like automobiles. The Industry 3.0,

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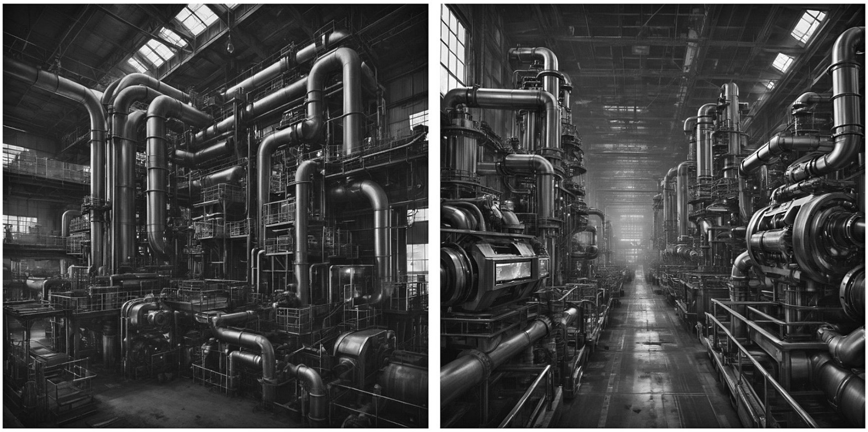


Industry 1.0 (Birth of Industrial revolution. Mechanized production, coal, steam power. Emergence of factories, mass production.)

Industry 2.0 (Electricity in Industrial revolution. Assembly line innovation. Increased productivity, efficiency, new industries)

Figure 1.1 Key differences and unique characteristics of industrial revolutions (Industry 1.0 and Industry 2.0)

Industry 3.0 (Digital revolution, electronic technologies & computer-based systems, emergence of internet, 3D printing, cloud etc.)

Industry 4.0 (Automation and data exchange. IoT, AI and Machine Learning – Technologies. Increased productivity and efficiency)

Figure 1.2 Key Differences and unique characteristics of industrial revolution (Industry 3.0 and Industry 4.0)

also known as the digital revolution, brought electronic technologies, computer-based systems, network, and the internet. The Industry 4.0 – fourth industrial revolution, commenced in the early years of the 21st century, emphasizing automation and data exchange, leading to artificial intelligence, Internet of Things, and machine learning [3]. The comparison is shown in Figure 1.2.

As we move to Industry 5.0, the human–tech partnership, the focus shifts to collaboration between humans and machines. This approach seeks

to balance the strengths of advanced technologies with human creativity, fostering a collaborative work environment. Industry 5.0 emphasizes customization, sustainability, decentralization, and flexibility, striving for increased efficiency and productivity while promoting social responsibility [4].

The sixth industrial revolution – Industry 6.0, builds on Industry 5.0 with advanced technologies like quantum computing and nanotechnology. It promises highly efficient solutions, new business models, advanced robotics, and enhanced safety. However, with these advancements come potential drawbacks and challenges, necessitating careful consideration of their impacts on production, management, and consumption of goods, services, and information. Industry 6.0 represents the continuous evolution and improvement of industry, with both exciting possibilities and considerations for responsible implementation [5]. Table 1.1 shows the characteristics, technologies, and key factors of various generations of the industrial revolution.

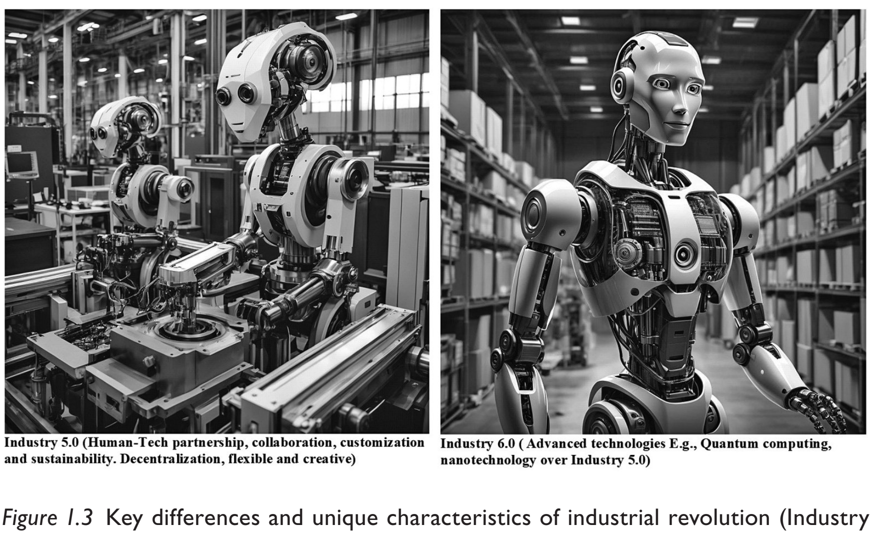
Both Industry 5.0 revolution and recent Industry 6.0 represent distinct phases in the evolution of industrial technologies, each marked by unique characteristics and advancements. In Industry 5.0, the emphasis is on fostering human–machine collaboration. This is evident in scenarios where advanced technologies such as artificial intelligence, robotics, and Industrial

Table 1.1 Characteristics, technologies, and key factors of various generations of industrial revolution

Industrial Revolution	*Characteristics*	*Technologies*	*Key Factors Driving Growth*
Industry 1.0	Late 18th to mid-19th century	Mechanized production, coal, steam power, emergence of factories	Mass production, industrial giants (e.g., cotton mills, ironworks)
Industry 2.0	Late 19th to early 20th century	Electricity, assembly line	Increased productivity, efficiency, new industries (e.g., automobile)
Industry 3.0	Mid-20th century	Electronic technologies, computer-based systems, automation	Emergence of the internet, 3D printing, big data, cloud computing
Industry 4.0	Early 21st century	Automation, data exchange	IoT, AI, ML, 3D printing, big data, cloud computing
Industry 5.0	Ongoing transition	Human–tech partnership, emphasis on human creativity, AI, robotics, IoT	Collaboration, customization, sustainability, decentralization, flexibility
Industry 6.0	Future concept	Advanced technologies (e.g., quantum computing, nanotechnology) over Industry 5.0	Increased efficiency, effective problem-solving, advanced robotics, safety, security, blockchain

Internet of Things work in tandem with human creativity. For instance, in smart manufacturing setups, human workers collaborate with robots to enhance efficiency and streamline production processes. The focus on product customization is exemplified by companies employing AI algorithms to tailor products according to individual customer preferences, ensuring a personalized and satisfying consumer experience. Sustainability takes center stage in Industry 5.0, where manufacturing processes are designed to minimize environmental impact, aligning with the growing global emphasis on eco-friendly practices. Decentralization is observed in the shift towards distributed production, bringing manufacturing closer to the point of consumption, thereby reducing transportation needs [6]. A comparison of Industry 5.0 and Industry 6.0 is shown in Figure 1.3.

On the other hand, Industry 6.0 represents a future concept built upon latest advancements, for instance quantum computing and nanotech. Here, the focus shifts towards achieving enhanced efficiency through cutting-edge solutions. For instance, the implementation of quantum computing in supply chain management can optimize complex logistics, ensuring quicker and more accurate decision-making processes. The consideration for increased safety and security in Industry 6.0 is illustrated by the incorporation of advanced robotics in manufacturing plants. These robotic systems, equipped with sophisticated safety features, can operate alongside human workers, reducing the risk of accidents and enhancing overall workplace safety. Additionally, Industry 6.0 revolution opens avenues for novel business models, exemplified by the practice of blockchain technology for protected and consistent data sharing. Companies can implement blockchain to ensure transparency in the supply chain, fostering trust



Industry 5.0 (Human-Tech partnership, collaboration, customization and sustainability. Decentralization, flexible and creative)

Industry 6.0 (Advanced technologies E.g., Quantum computing, nanotechnology over Industry 5.0)

Figure 1.3 Key differences and unique characteristics of industrial revolution (Industry 5.0 and Industry 6.0)

Table 1.2 A comparison of Industry 5.0 and Industry 6.0

Aspect	*Industry 5.0*	*Industry 6.0*
Technological Basis	AI, robotics, IoT	Advanced technologies (quantum computing, nanotech)
Human–Machine Balance	Emphasis on human creativity and innovation	Enhanced efficiency through advanced technologies
Focus	Collaboration between humans and machines	Efficient problem-solving with advanced solutions
Product Customization	High emphasis on customized products and services	Potential for more efficient and effective solutions
Sustainability	Strong focus on sustainable manufacturing processes	Consideration for increased safety and security
Decentralization	Distributed production and manufacturing	Leveraging advanced robotics for improved processes
Flexibility	Quick adaptation to changing market conditions	Improved adaptability with advanced technological tools
Unique Characteristics	Collaboration Customization Sustainability Decentralization Flexibility	Advanced technologies (quantum computing, nanotech) Increased safety and security Potential for new business models

among consumers [7]. Table 1.2 displays a comparison of Industry 5.0 and Industry 6.0 in a detailed way.

Industry 5.0 emphasizes collaboration as a cornerstone, offering a compelling vision for the future of work, innovation, customization, sustainability, decentralization, and flexibility, while Industry 6.0 builds upon these foundations with an emphasis on modern technologies, safety, security, and the potential for innovative business models. Both phases contribute to the ongoing transformation of the industrial landscape, each offering unique solutions to the challenges and opportunities of the digital era.

1.2 FOUNDATIONS OF CONNECTIVITY: UNRAVELING THE POWER OF IIOT

This section delves into the foundational aspects of the IIoT (Industrial Internet of Things) and explores its transformative power across various industries. Here, we gain a comprehensive understanding of how the IIoT establishes the groundwork for enhanced connectivity within industrial ecosystems. It unravels the capabilities of IIoT in connecting physical devices, machinery, and systems, facilitating real-time data exchange and communication.

The exploration begins with an overview of the key components of IIoT and its role in shaping the modern industrial landscape. It delves into the unified integration of sensors, actuators, and smart devices, illustrating how these elements form the backbone of connected systems. This also examines the potential of IIoT in unlocking valuable insights from the data generated by interconnected devices, laying the groundwork for informed decision-making and predictive maintenance strategies.

Real-world examples and case studies highlight the practical applications of IIoT, showcasing its impact on optimizing operational processes, improving efficiency, and enabling proactive problem-solving.

1.2.1 IIoT for future generation information systems

The role of the IIoT within the context of Future Generation Information Systems (FGIS) is instrumental in shaping the landscape of interconnected, intelligent, and data-driven systems. The IIoT plays a pivotal role, contributing to the evolution and advancement of FGIS across multiple dimensions.

- Connectivity and Integration: IIoT facilitates seamless connectivity and integration of devices, sensors, and systems within FGIS. This interconnectedness forms the basis for the efficient exchange of data and information, enabling a more cohesive and responsive information system [8].
- Real-time Data Acquisition: In FGIS, the utilization of IIoT allows for real-time data acquisition from various sources. Sensors embedded in industrial equipment, infrastructure, and other critical components enable continuous monitoring, ensuring that the information systems are fed with up-to-date and relevant data [9].
- Decision Support Systems: IIoT device generated data in FGIS serves as valuable inputs for decision support systems. Through the utilization of advanced analytics and machine learning, FGIS can drive informed decision-making, streamline processes, and forecast future trends, thereby augmenting the overall intelligence of the system [10].
- Efficiency and Optimization: IIoT contributes to the optimization of processes and workflows within FGIS. Through data-driven insights, efficiency gains can be achieved in resource utilization, energy management, and overall operational performance [11].
- Predictive Maintenance: Within FGIS, IIoT serves a pivotal function in executing predictive maintenance strategies. Through ongoing monitoring of equipment and infrastructure conditions, predictive analytics can foresee maintenance requirements, thus reducing downtime and optimizing asset longevity [12].
- Security and Reliability: IIoT in FGIS requires robust cybersecurity measures to ensure the safety, security, and consistency of

interconnected systems. As FGIS evolves, addressing cybersecurity challenges becomes integral to safeguarding sensitive information and maintaining the integrity of the information systems [13].

- Interdisciplinary Collaboration: IIoT fosters interdisciplinary collaboration within FGIS by bringing together expertise in information technology, industrial processes, and data science. This collaborative approach enables the development of comprehensive solutions that address the complex challenges of future information systems [14].

The integration of IIoT within Future Generation Information Systems (FGIS) plays a crucial role across various aspects, as outlined in Table 1.3. Each aspect highlights the specific role of IIoT and its applications in shaping the landscape of interconnected and intelligent information systems. Table 1.3 summarizes the role of IIoT in FGIS and Applications in a detailed way.

1.2.2 Intelligent automation: the strategic integration of artificial intelligence in industry

Intelligent Automation refers to the strategic integration of AI within the industrial landscape. It involves the seamless collaboration of AI

Table 1.3 The integration of IIoT within Future Generation Information Systems (FGIS)

Aspect	*Role of IIoT in FGIS*	*Applications*
Connectivity and Integration	Facilitates seamless connection of devices and systems	Integration of sensors and devices for cohesive information systems
Real-time Data Acquisition	Enables continuous monitoring for up-to-date data	Sensors in industrial equipment providing real-time information
Decision Support Systems	Provides valuable inputs for informed decision-making	Leveraging analytics and machine learning for decision support
Efficiency and Optimization	Contributes to process and workflow optimization	Resource utilization, energy management, and operational efficiency
Predictive Maintenance	Monitors equipment conditions for predictive analytics	Anticipating maintenance needs to minimize downtime
Security and Reliability	Ensures robust cybersecurity measures for system integrity	Implementing security protocols to safeguard information systems
Interdisciplinary Collaboration	Fosters collaboration across IT, industrial processes, and data science	Bringing expertise together for comprehensive solutions
Connectivity and Integration	Facilitates seamless connection of devices and systems	Integration of sensors and devices for cohesive information systems

technologies with existing processes to enhance operational efficiency, decision-making, and overall productivity in different industries. Through the deployment of AI algorithms and machine learning, intelligent automation enables machines to learn, adapt, and optimize tasks autonomously. This integration empowers industries to streamline complex operations, minimize errors, and improve overall performance, marking a significant shift towards smarter and more responsive industrial systems [15].

Integrating AI technologies into Industry 6.0 involves leveraging advanced AI capabilities to enhance automation, decision-making, and overall efficiency within industrial processes. Here are the key strategies for integrating AI in Industry 6.0:

Smart Manufacturing Systems

- Deploy AI-driven smart manufacturing systems that harness ML (machine learning) algorithms to analyze data sourced from diverse sensors, devices, and production lines [16].
- Develop adaptive systems that can optimize production schedules, resource allocation, and energy consumption based on real-time data [16].

Predictive Maintenance

- Utilize AI-based algorithms to predict equipment's failures and maintain schedules proactively [17].
- Analyze historical and real-time data from various sensors to recognize patterns indicative of potential issues, enabling timely interventions [17].

AI-Enabled Robotics

- Integrate AI into industrial robotics for enhanced automation and flexibility [18].
- Implement robotic systems with machine learning capabilities to adapt to changing tasks and collaborate seamlessly with human workers [19].

Supply Chain Optimization

- Employ AI for optimizing supply chain processes by forecasting demand, managing inventory efficiently, and optimizing logistics.
- Implement AI-driven predictive analytics to enhance decision-making in supply chain management [20].

Quality Control and Assurance

- Implement AI-based image recognition and computer vision systems for quality control.

- Integrate ML (machine learning) algorithms to perform analysis from sensors to detect defects and anomalies in real-time [21].

Cognitive Manufacturing

- Develop cognitive manufacturing systems that combine AI, data analytics, and human expertise [22].
- Utilize AI to analyze unstructured data, such as text and images, to derive valuable insights and inform decision-making [22].

AI-Driven Decision Support Systems

- Create decision support systems driven by AI to deliver actionable insights tailored for managers and operators.
- Implement algorithms that analyze complex datasets to optimize production parameters and improve overall operational efficiency [23].

Table 1.4 summarizes the key integration strategies for incorporating Artificial Intelligence technologies in Industry 6.0, along with the corresponding actions and applications for each strategy.

Table 1.4 Key integration strategies for incorporating artificial intelligence technologies in Industry 6.0

Integration Strategy	*Key Actions and Applications*
Data Integration and Analysis	• Collect comprehensive data from various sources • Clean and preprocess data for AI algorithms • Implement big data analytics for insights.
Machine Learning Applications	• Predictive maintenance using ML models. • Quality control through AI monitoring. • Production optimization with machine learning.
Autonomous Systems	• Integrate AI-powered robotics for automation. • Implement AI in autonomous vehicles.
Decision Support Systems	• Develop AI-based decision support systems. • Optimize supply chain operations with AI.
Natural Language Processing (NLP)	• Enable human–machine interaction with NLP. • Implement voice-activated systems using AI.
Edge Computing	• Deploy AI models on edge devices for real-time analysis. • Utilize edge computing for local data processing.
Cybersecurity and AI	• Implement AI-powered cybersecurity measures. • Use AI for anomaly detection and threat response.
Continuous Learning and Adaptation	• Employ reinforcement learning algorithms. • Implement adaptive control systems for optimization.
Human–AI Collaboration	• Provide training for workforce collaboration with AI. • Design user-friendly interfaces for interaction.
Regulatory Compliance and Ethical Considerations	• Establish AI governance frameworks. • Ensure transparency and accountability in AI use.

1.3 INDUSTRY 6.0: THE NEXT FRONTIER OF INDUSTRIAL REVOLUTION WITH IIOT, AI AND DATA ANALYTICS, QUANTUM COMPUTING

The emergence of Industry 6.0 marks the next frontier of the industrial revolution, characterized by the seamless integration of Industrial Internet of Things (IIoT), Artificial Intelligence (AI), and Data Analytics. This transformative phase is set to redefine industrial processes, unlocking unprecedented levels of efficiency, intelligence, and connectivity across diverse sectors.

Figure 1.4 illustrates the interconnected nature of IIoT, AI, and data analytics in Industry 6.0 and their collective impact on various aspects of industrial operations.

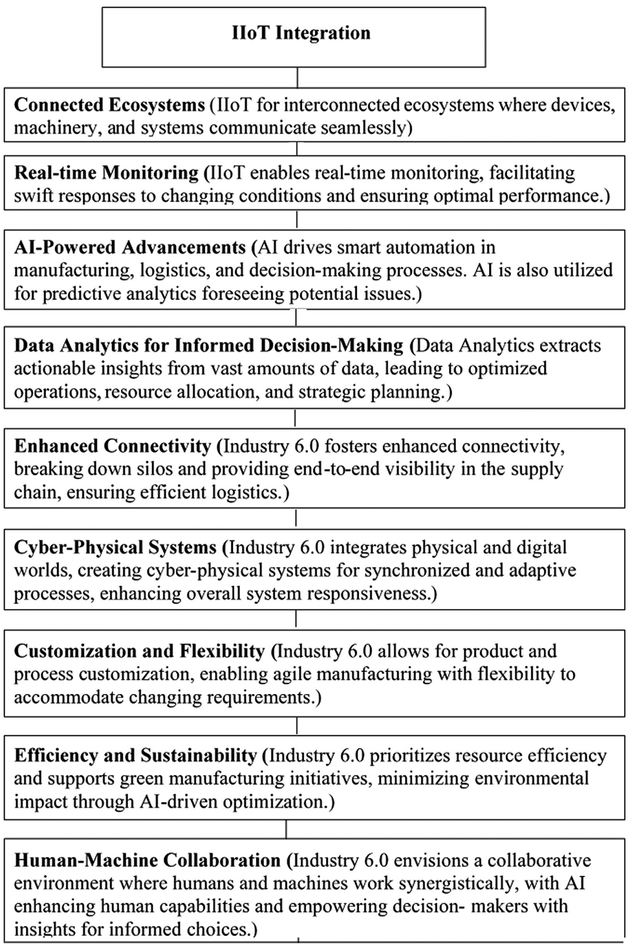


Figure 1.4 Interconnected nature of IIoT, AI, and data analytics

IIoT Integration

- Connected Ecosystems: Industry 6.0 leverages IIoT to create interconnected ecosystems where devices, machinery, and systems communicate seamlessly.
- Real-time Monitoring: IIoT enables seamless real-time monitoring of industrial processes, allowing for agile responses to dynamic conditions and ensuring peak performance at all times [24].

AI-Powered Advancements

- Smart Automation: AI takes center stage in Industry 6.0, driving smart automation in manufacturing, logistics, and decision-making processes [25].
- Predictive Analytics: Utilizing AI for predictive analytics, Industry 6.0 can foresee potential issues, enabling proactive problem-solving and reducing downtime [26].

Leveraging Data Analytics for Informed Decision-Making

- Extracting Actionable Insights: Data Analytics serves as a critical tool for extracting actionable insights from the vast volume of data generated within industrial environments [27].
- Optimized Operations: Informed decision-making, powered by data analytics, leads to optimized operations, resource allocation, and strategic planning [28].

Enhanced Connectivity

- Interconnected Systems: Industry 6.0 fosters enhanced connectivity, breaking down silos between different components of the industrial ecosystem [29].
- Supply Chain Visibility: Improved connectivity provides end-to-end visibility in the supply chain, ensuring efficient logistics and reducing lead times [30].

Cyber-Physical Systems

- Bridging the Physical and Digital Realms: Industry 6.0 dissolves the boundaries between physical and digital domains, fostering the development of cyber-physical systems that harmonize effortlessly [31].
- Synchronized Processes: Cyber-physical systems enable synchronized and adaptive processes, enhancing overall system responsiveness [32].

Customization and Flexibility

- Product and Process Customization: Industry 6.0 thrives on customization, allowing for tailored products and adaptable processes to meet evolving market demands [33].
- Agile Manufacturing: Flexibility in manufacturing processes enables rapid adjustments to accommodate changing requirements and consumer preferences.

Efficiency and Sustainability

- Resource Efficiency: Industry 6.0 prioritizes resource efficiency through AI-driven optimization and sustainable practices [34].
- Green Manufacturing: The integration of AI and IIoT supports green manufacturing initiatives, minimizing environmental impact [35].

Human–Machine Collaboration

- Augmented Workforce: Industry 6.0 foresees a harmonious collaboration between humans and machines, where artificial intelligence (AI) amplifies human capabilities [36].
- Empowering Decision-Makers: AI empowers decision-makers by providing valuable insights, enabling them to make informed choices in intricate industrial settings [37].

Table 1.5 summarizes examples of the futuristic approach in Industry 6.0, showcasing the applications of IIoT in various aspects of industrial processes.

1.3.1 Applications of IIoT, AI, data analytics, and quantum computing in manufacturing, food, and healthcare industries within Industry 6.0

In the context of Industry 6.0, the convergence of Industrial Internet of Things, artificial intelligence, data analytics, and quantum computing is revolutionizing manufacturing, food, and healthcare industries. In manufacturing, IIoT sensors facilitate predictive maintenance, process optimization and real-time monitoring, while AI enhances production scheduling and resource utilization [38]. Data analytics analyzes historical data for efficient decision-making, and quantum computing tackles complex optimization challenges. In the food industry, IIoT ensures quality by monitoring storage conditions, AI with computer vision inspects products, and Data Analytics optimizes production based on consumer preferences. Quantum computing enhances data encryption in the supply chain. In healthcare manufacturing, IIoT monitors equipment precision, AI predicts maintenance needs,

Table 1.5 Key integration strategies for incorporating artificial intelligence technologies in Industry 6.0

Aspect	*Futuristic Approach Example in Industry 6.0*
Smart Factories	In Industry 6.0, smart factories leverage IIoT for real-time monitoring and predictive maintenance, optimizing production processes.
Autonomous Robots in Manufacturing	Industry 6.0 introduces autonomous robots with IIoT sensors for tasks like assembly and quality control, collaborating with human workers.
Supply Chain Orchestration	Futuristic supply chains in Industry 6.0, powered by IIoT, enable dynamic adjustments in logistics, inventory, and demand forecasting in real-time.
Digital Twins for Equipment Monitoring	Digital twins in Industry 6.0 use IIoT to create virtual replicas, facilitating detailed monitoring, performance analysis, and simulations for optimization.
AI-Enhanced Predictive Maintenance	AI algorithms analyze IIoT data for predictive maintenance, reducing downtime and extending machinery lifespan in Industry 6.0.
Energy-Efficient Manufacturing	IIoT-driven energy monitoring and AI optimization contribute to energy-efficient manufacturing processes in Industry 6.0.
Collaborative Human–Machine Workspaces	Industry 6.0 envisions collaborative workspaces where IIoT enables machines to understand human gestures and adapt to working styles.
Edge Computing for Real-Time Processing	IIoT in Industry 6.0 incorporates edge computing, ensuring real-time data processing for applications like autonomous vehicles and quality control.

data analytics optimizes processes, and quantum computing ensures secure patient data [39]. These applications in Industry 6.0 drive automation, predictive capabilities, enhanced decision-making, optimized processes, and heightened security across diverse industrial sectors, steering in a modern era of effectiveness and innovation.

Manufacturing Industry

- IIoT: In manufacturing, IIoT sensors embedded in machinery monitor equipment health and performance in real-time. For instance, a smart manufacturing plant may use IIoT to track the status of production lines, predict equipment failures, and optimize maintenance schedules [40].
- AI: AI algorithms in manufacturing analyze data from IIoT sensors to optimize production processes [41]. For example, AI can dynamically adjust production schedules based on demand fluctuations, leading to more efficient resource utilization and reduced waste.
- Data Analytics: Data analytics in manufacturing utilizes historical production data to identify patterns and trends. This can aid in

predicting market demand, optimizing inventory levels, and improving overall supply chain efficiency [42].
- Quantum Computing: Quantum computing can be applied to solve complex optimization problems in manufacturing, such as optimizing supply chain routes, scheduling production tasks, and improving energy efficiency [43].

Food Industry

- IIoT: In the food industry, IIoT can be employed to monitor and maintain optimal conditions in storage facilities. For example, sensors can track temperature and humidity levels to ensure the quality and safety of perishable goods during transportation [44].
- AI: AI applications in the food industry include quality control using computer vision. AI-enabled cameras can conduct thorough inspections of food products, guaranteeing that only top-quality items are delivered to consumers. [45].
- Data Analytics: Data analytics in the food industry can analyze consumer preferences and buying patterns. This information helps in demand forecasting, allowing producers to optimize production and reduce waste [46].
- Quantum Computing: Quantum computing can enhance the encryption and security of food supply chain data, ensuring the integrity of information related to food safety and traceability [47].

Healthcare Industry

- IIoT: In healthcare manufacturing, IIoT can be used to monitor and maintain the condition of manufacturing equipment, ensuring the production of precise and high-quality medical devices [48].
- AI: AI applications in healthcare include predictive maintenance for medical equipment. AI algorithms can analyze data from IIoT sensors on medical devices to predict potential failures, reducing downtime and improving patient care [49].
- Data Analytics: Data analytics in healthcare manufacturing analyzes production data to identify opportunities for process optimization, leading to increased efficiency and cost savings [50].
- Quantum Computing: Quantum computing can enhance the security of patient data, ensuring the confidentiality and integrity of sensitive healthcare information [51].

Table 1.6 provides concise examples of how IIoT, AI, data analytics, and quantum computing can be applied in the manufacturing, food, and healthcare industries within the framework of Industry 6.0.

Table 1.6 IIoT, AI, data analytics, and quantum computing applications in various industries

Industry	*IIoT*	*AI*	*Data Analytics*	*Quantum Computing*
Manufacturing	IIoT sensors monitor machinery health; predict equipment failures.	AI optimizes production schedules based on demand fluctuations.	Data analytics analyzes factory data for optimization.	Quantum computing used for complex optimization problems.
Food	IIoT monitors storage conditions; ensures quality of perishable goods.	AI with computer vision inspects food products for defects.	Data analytics analyzes consumer preferences for demand forecasting.	Quantum computing enhances data encryption in supply chain.
Healthcare	IIoT monitors manufacturing equipment for precision in medical device production.	AI predicts maintenance needs for medical equipment, reducing downtime.	Data analytics optimizes healthcare manufacturing processes.	Quantum computing enhances security of patient data.

1.3.2 Revolutionizing industry 6.0: The synergistic power of IIOT, AI, data analytics, and quantum computing in automated industrial processes

The integration of IIoT, AI, data analytics, and quantum computing holds significant potential to automate and enhance industrial processes in the context of Industry 6.0. Here's a brief overview of the significance of each technology:

IIoT (Industrial Internet of Things)

- Edge Computing Integration: The latest development in IIoT entails the integration of edge computing, facilitating data processing in close proximity to the data source. This approach minimizes latency and elevates real-time decision-making capabilities within industrial processes. [52].
- 5G Connectivity: The emergence of 5G technology has significantly bolstered the capabilities of IIoT by delivering ultra-fast and dependable connectivity. This enables seamless communication between devices, fostering a more interconnected and responsive industrial ecosystem [53].

- Cyber-Physical Systems (CPS): IIoT has evolved towards the integration of cyber-physical systems, creating a more symbiotic relationship between digital and physical components. This integration enhances the adaptability and responsiveness of industrial processes [54].

AI (Artificial Intelligence)

- Explainable AI (XAI): In response to the need for transparency in AI decision-making, recent advancements include Explainable AI. This fosters stakeholders' comprehension and trust in AI algorithm decisions, a particularly crucial aspect in industrial contexts where decision outcomes carry significant consequences [55].
- AI for Sustainability: Beyond efficiency, AI is now being harnessed to drive sustainability in industrial processes. AI algorithms are optimizing energy consumption, waste reduction, and environmental impact, aligning with global efforts towards sustainable industrial practices [56].
- Human–AI Collaboration: The focus is shifting towards creating synergies between human workers and AI systems. Advanced AI interfaces and collaborative robots are being developed to augment human capabilities in industrial environments, fostering a more efficient and adaptive workforce [57].

Data Analytics

- Exponential Growth in Data Lakes: The scale of data generated by IIoT has led to the widespread adoption of data lakes – large repositories that can store vast amounts of structured and unstructured data. Advanced analytics platforms are then employed to extract valuable insights from these expansive datasets [58].
- Machine Learning-Powered Analytics: Machine learning models are increasingly being integrated into data analytics processes, enabling the identification of complex patterns and trends that may go unnoticed by traditional analytics approaches. This enhances the predictive capabilities of industrial operations [59].
- Prescriptive Analytics: Going beyond descriptive and predictive analytics, the industry is now embracing prescriptive analytics. These systems not only forecast future trends but also recommend actions to optimize processes, providing actionable intelligence for proactive decision-making [60].

Quantum Computing

- Quantum Supremacy Milestones: Quantum computing has achieved significant milestones in terms of qubit stability and coherence. This

progress is paving the way for more practical applications in industrial optimization, simulation, and complex problem-solving [61].

- Hybrid Quantum-Classical Systems: To address the current limitations of quantum computers, hybrid systems that combine classical and quantum computing are being developed. This approach leverages the strengths of both paradigms, making quantum computing more accessible for industrial applications [62].
- Quantum Machine Learning: Quantum machine learning algorithms are emerging as powerful tools for data analysis. These algorithms leverage quantum parallelism to process vast datasets at unprecedented speeds, opening new possibilities for industrial data optimization and decision-making [63].

Industry 6.0 is a dynamic concept, and specific applications may vary across industries. The following applications and examples in Table 1.7 are

Table 1.7 Overall significance of IIoT, AI, data analytics, and quantum computing in Industry 6.0

Significance	*Applications/ Examples*
Automation	• Smart factories leveraging IIoT for real-time monitoring and control. • Autonomous systems in manufacturing, reducing the need for manual intervention. • Automated supply chain processes with real-time tracking and optimization.
Predictive Capabilities	• Predictive maintenance in manufacturing, anticipating equipment failures. • AI algorithms analyzing historical and real-time data to forecast demand fluctuations. • Early identification of potential issues in the production process before they impact operations.
Enhanced Decision-Making	• Real-time insights from IIoT, AI, and data analytics aiding decision-makers. • Adaptive production scheduling based on AI analysis of market trends and consumer behavior. • Improved decision-making in supply chain management, optimizing inventory levels and logistics.
Optimized Processes	• AI-driven optimization of production parameters for efficiency and quality improvement. • Dynamic adjustment of manufacturing processes based on IIoT data for resource utilization. • Supply chain processes designed for cost savings, reduced waste, and sustainability.
Security &Efficiency	• Quantum computing enhancing data security through advanced encryption methods. • Solving complex optimization problems in logistics, scheduling, and resource allocation. • Improved operational efficiency through the collaborative use of technologies like digital twins and AI.

illustrative and represent potential applications in the evolution towards smarter and more connected industrial ecosystems.

1.4 HARMONY IN INDUSTRY 6.0: UNVEILING THE SYMPHONY OF IIOT, AI, AND DATA ANALYTICS

In the world of technology, IIoT (Industrial Internet of Things) and AI (Artificial Intelligence) are like a powerful duo, revolutionizing industries by combining connectivity with intelligence. This sub-section explores how their collaboration is reshaping industrial processes and sparking significant changes across different sectors.

Industrial Internet of Things (IIoT) brings together smart devices, sensors, and communication tech in industrial settings, making operations more efficient. Unlike the consumer-focused Internet of Things (IoT), IIoT is all about improving and streamlining industrial processes, enabling devices to communicate and share data instantly.

1.4.1 The futuristic components of the IIoT ecosystem

The following Figure 1.5 provides a simplified block diagram description of the futuristic components of the IIoT ecosystem in Industry 6.0:

Sensors and Devices: IIoT relies on a network of sensors and devices placed within machinery and industrial equipment. These sensors act like senses, collecting important data on factors like temperature, pressure, and vibration that are vital for industrial operations. [64].

The development and adoption of futuristic technologies are ongoing, as listed in Table 1.8, and their practical use in Industry 6.0 will depend on further advancements and industry-specific requirements.

Connectivity: Connectivity is vital for IIoT, with technologies such as 5G ensuring fast, reliable connections for smooth communication between devices in industrial settings. Some advanced connectivity options for Industry 6.0 include the following:

- 6G Technology: The evolution beyond 5G, 6G is anticipated to provide even faster and more reliable connectivity. It will be a key enabler for Industry 6.0, ensuring ultra-low latency and supporting a massive number of connected devices [65, 66].
- Edge Computing Networks: Enhanced edge computing capabilities will become integral, enabling data processing and analytics closer to the data source. [67].
- Swarm Intelligence Networks: Inspired by natural swarm behavior, Industry 6.0 may leverage swarm intelligence in IIoT and AI systems.

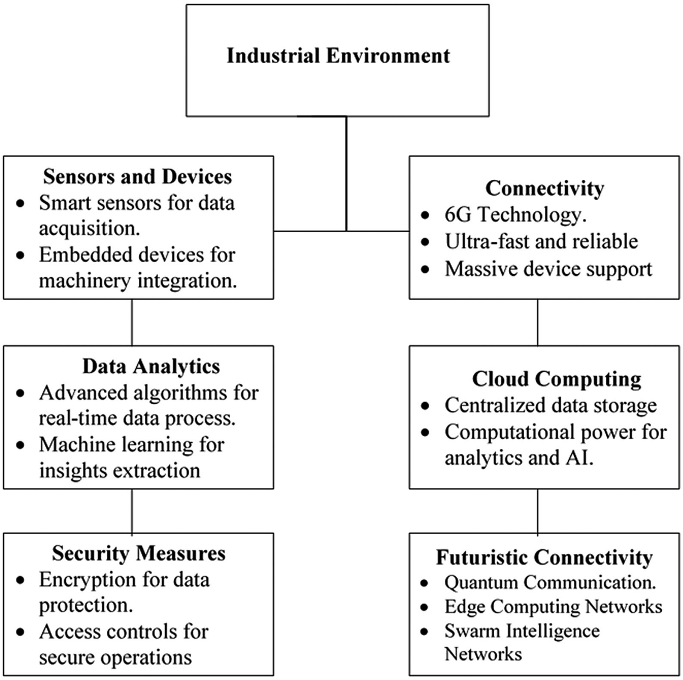


Figure 1.5 Simplified diagram for futuristic components of the IIoT ecosystem in Industry 6.0

Devices collaboratively communicate and make decentralized decisions, enhancing efficiency and adaptability [68].

- Quantum Communication Networks: Quantum communication offers unprecedented security and speed. In Industry 6.0, quantum key distribution and quantum entanglement could be used to secure communication channels, crucial for sensitive industrial data [69].
- Neuromorphic Computing Networks: Drawing inspiration from the human brain, neuromorphic computing could revolutionize AI in Industry 6.0. It involves networks of artificial neurons that can process information more efficiently, improving AI capabilities [70].
- Digital Twins and Virtual Reality Integration: The coupling of digital twin technologies with virtual reality interfaces will create immersive and interactive environments for monitoring and controlling industrial processes. This integration enhances the understanding and management of complex systems [71].
- Blockchain-Enabled Networks: Blockchain technology ensures secure, transparent, and tamper-resistant transactions. In Industry 6.0, it could be integrated into IIoT and data analytics systems for secure and transparent supply chain management and data sharing [72].

Table 1.8 List of futuristic sensors and devices for IIoT and Industry 6.0

Futuristic Sensors/ Devices	*Description*
Nanosensors	Miniaturized sensors operating at the nanoscale, capable of detecting molecular-level changes in industrial processes.
Quantum Sensors	Leveraging principles of quantum mechanics, these sensors offer ultra-sensitive measurements for parameters like temperature, pressure, and magnetic fields, enabling high-precision monitoring.
Smart Drones	Unmanned aerial vehicles equipped with advanced sensors for aerial inspections, monitoring, and data collection in large industrial facilities.
Augmented Reality (AR) Glasses	AR glasses provide real-time data overlays onto the physical environment, enhancing worker efficiency in tasks like equipment maintenance, inspection, and troubleshooting.
Flexible Electronics	Bendable and stretchable electronics for sensor applications, allowing integration into irregular surfaces or moving components, expanding monitoring capabilities in dynamic industrial settings.
Haptic Feedback Devices	Devices providing tactile feedback to operators based on IIoT data, enhancing human–machine interaction in industrial control and monitoring applications.
Swarm Robotics	A collective of small, interconnected robots working collaboratively, equipped with sensors for tasks such as environmental monitoring, inventory management, and cooperative assembly in smart factories.
Hyperspectral Imaging	Sensors capturing data across a wide range of the electromagnetic spectrum, enabling detailed analysis of materials and processes in industries like agriculture, pharmaceuticals, and quality control.
Edge AI Processors	Dedicated processors integrated into IIoT devices for on-device AI inference, reducing latency and enhancing real-time decision-making capabilities directly at the edge of the industrial network.
Smart Fabrics	Textiles embedded with sensors for monitoring environmental conditions, worker health, and safety. Applications include smart uniforms for workers in hazardous environments or for health monitoring in medical settings.

- AI-Driven Communication Networks: AI algorithms are poised to play a pivotal role in optimizing communication networks, dynamically adapting to evolving conditions, predicting failures, and efficiently allocating resources. This ensures a seamless connectivity experience in the realm of Industry 6.0 [73].
- Bio-Inspired Networks: Mimicking biological systems, bio-inspired networks may play a role in Industry 6.0 connectivity. Algorithms inspired by genetic algorithms, ant colonies, or neural networks could optimize communication and decision-making processes [74].
- Holographic Communication: Advancements in holographic technology may introduce holographic communication interfaces, providing

an innovative way for industrial stakeholders to visualize and interact with data in real-time [75].

Table 1.9 provides a concise overview of the futuristic connectivity options in Industry 6.0, including their capacities and coverage in its applications.

Data Analytics: IIoT unleashes immense volumes of data, and its true power lies in proficiently analyzing this data using advanced data analytics and machine learning algorithms. Through this analysis, valuable insights, patterns, and trends can be uncovered, driving informed decision-making and innovation. [76].

Cloud Computing: Cloud platforms form the digital infrastructure of IIoT, offering storage, computational power, and enabling real-time data access and scalability, thereby converting raw data into actionable intelligence through analytics solutions. [77].

Security Measures: Given the critical role of industrial operations, robust cybersecurity measures are imperative for IIoT implementation. This entails deploying encryption, implementing secure access controls, and maintaining continuous monitoring protocols. Such measures are essential for safeguarding against cyber threats and upholding the integrity and safety of industrial processes. [78].

1.4.2 Predictive maintenance in Industry 6.0

In the landscape of Industry 6.0, the convergence of IIoT, AI, and data analytics is reshaping traditional approaches to maintenance, ushering in an era of predictive maintenance. This transformative synergy harnesses the

Table 1.9 List of futuristic sensors and devices for IIoT and Industry 6.0

Futuristic Sensors/Devices	*Capacity and Coverage*
6G Technology	Ultra-low latency, massive device support.
Edge Computing Networks	Localized processing for real-time decision-making.
Swarm Intelligence Networks	Enhanced efficiency and adaptability.
Quantum Communication Networks	Unprecedented security and speed.
Neuromorphic Computing Networks	Improved AI capabilities.
Digital Twins and VR Integration	Interactive environments for better system understanding.
Blockchain-Enabled Networks	Enhanced security and transparency.
AI-Driven Communication Networks	Efficient resource allocation and adaptability.
Bio-Inspired Networks	Optimization based on genetic algorithms, ant colonies, etc.
Holographic Communication	Innovative visualization and interaction interfaces.

power of advanced technologies to anticipate and address potential equipment failures before they disrupt industrial processes. Here's an exploration of the key components and implications of predictive maintenance in the context of Industry 6.0:

- Harnessing the Power of IIoT with Smart Sensors and Connectivity: IIoT forms the foundation of predictive maintenance, with smart sensors embedded in machinery and industrial equipment [79]. These sensors continuously collect real-time data on crucial parameters, fostering seamless connectivity and communication across the industrial landscape.
- AI-Driven Predictions with Machine Learning Algorithms: AI plays a pivotal role in predictive maintenance, with machine learning algorithms analyzing vast datasets. These algorithms learn from historical patterns, enabling the prediction of potential failures by identifying anomalies, deviations, and degradation in equipment performance [80].
- Real-Time Data Analytics and Advanced Analytics Platforms: Data analytics processes the continuous stream of information generated by IIoT devices. It extracts valuable insights, detects patterns, and provides a comprehensive understanding of equipment health, allowing for informed decision-making [81].
- Condition Monitoring and Proactive Interventions by Continuous Monitoring: Predictive maintenance involves continuous monitoring of equipment conditions, moving beyond fixed schedules. This real-time approach allows for proactive interventions based on the actual health and performance of machinery [82].
- Predictive Insights for Operational Excellence and Efficiency: The predictive insights derived from the synergy of IIoT, AI, and data analytics contribute to operational excellence. Industries can optimize maintenance schedules, minimize downtime, and enhance overall efficiency [83].
- Scalability with Cloud Computing: Cloud computing acts as the virtual backbone, providing scalable storage and computational power. This scalability enables industries to deploy predictive maintenance solutions across diverse and extensive industrial operations [84].
- Cost Savings and Resource Optimization by Efficient Resource Allocation: Predictive maintenance aids in optimizing resource allocation by focusing efforts where they are most needed. This strategic allocation results in cost savings through reduced downtime and targeted interventions [85].
- Enhanced Safety Measures: By addressing potential equipment failures before they escalate, predictive maintenance enhances safety measures in industrial environments. It mitigates the risks associated with unexpected breakdowns, contributing to a safer working environment [86].

The predictive maintenance in Industry 6.0 represents a paradigm shift, leveraging the symbiotic relationship between IIoT, AI, and data analytics. This synergy not only ensures the continuous and efficient operation of industrial machinery but also sets the stage for a more resilient, connected, and intelligent industrial ecosystem.

1.4.3 Predictive maintenance approaches classification

In the context of Industry 6.0, the various approaches to predictive maintenance classes can be significantly improved through the integration of advanced technologies such as AI, IIoT, and data analytics. Here's how each class can benefit from these innovations:

- Single Approaches: Enhance real-time monitoring through IIoT sensors, enabling the continuous collection of equipment health data. Implement AI algorithms for more accurate predictions based on historical and real-time data [87].
- Knowledge-Based: Integrate AI to enhance the knowledge base with machine learning models that continuously learn and adapt to evolving conditions. Utilize IIoT for real-time knowledge updates from the field [88].
- Physics-Based: Combine physics-based models with IIoT sensor data for more accurate representation of equipment conditions. Implement AI for dynamic adjustments to physics-based models based on real-time variations [89].
- Data-Driven and Statistic-Based Approaches: Leverage big data analytics for in-depth analysis of historical and real-time data. Utilize AI for more sophisticated statistical modeling, enabling better anomaly detection and predictive insights [90].
- Stochastic-Based Approaches: Incorporate IIoT data streams to capture the stochastic nature of equipment behavior. Implement advanced analytics and AI to improve the accuracy of stochastic models for predictive maintenance [91].
- ML-Based Approaches: Enhance machine learning models with continuous learning capabilities using real-time data from IIoT sensors. Implement explainable AI to provide insights into model decisions [92].
- Hybrid Approaches: Integrate multiple sources of data, including IIoT, to create a comprehensive dataset for hybrid models. Use AI to dynamically adjust the weighting of different models based on changing conditions [93].
- Multiple Knowledge/Physics/Data-Based Approaches: Improvement: Implement federated learning techniques, allowing models to be trained collaboratively across distributed IIoT devices. This ensures up-to-date knowledge, physics, and data-based approaches [94].

- Knowledge-Data/Physics-Data-Based Approaches: Improvement: Enhance knowledge and physics-based models with real-time data inputs from IIoT devices. Utilize AI for seamless integration and adaptation of data into existing knowledge and physics-based frameworks [95].
- Physics/Data-Physics-Based Approaches: Improvement: Integrate physics-based models with data-driven insights using AI. Ensure continuous learning and adaptation of the hybrid model to changing industrial conditions [96].

Here's a simplified branch diagram (Figure 1.6) illustrating the improvement of predictive maintenance classes in Industry 6.0 through the integration of advanced technologies:

In summary, Industry 6.0 can improve predictive maintenance classes by seamlessly integrating IIoT for real-time data, leveraging AI for advanced analytics and machine learning, and using data analytics to enhance decision-making capabilities. This integration ensures a more dynamic, adaptive, and efficient predictive maintenance strategy for the evolving industrial landscape.

1.5 PRACTICAL APPLICATIONS: CASE STUDIES HIGHLIGHTING SUCCESSFUL IMPLEMENTATIONS

Practical applications of the seamless integration of IIoT, AI, and data analytics have yielded remarkable success across diverse industries. One compelling case study involves the orchestration of these technologies in a harmonious symphony, exemplified by their collaborative impact on predictive maintenance in the mining sector, particularly in the context of grinding mills. In this application, the amalgamation of IIoT sensors for real-time data collection, advanced AI algorithms for predictive analysis, and sophisticated data analytics techniques has revolutionized maintenance strategies. Traditional curative and preventive maintenance methods, susceptible to inefficiencies and downtime, are replaced by a dynamic, predictive maintenance model. By leveraging machine learning algorithms, including deep learning, this approach not only optimizes maintenance schedules but also prevents equipment failures, resulting in enhanced operational efficiency, reduced downtime, and improved cost-effectiveness. This case study serves as a beacon, illuminating the transformative power of synergizing IIoT, AI, and data analytics, offering a glimpse into a future where industries can seamlessly navigate challenges and elevate their performance through the intelligent integration of cutting-edge technologies.

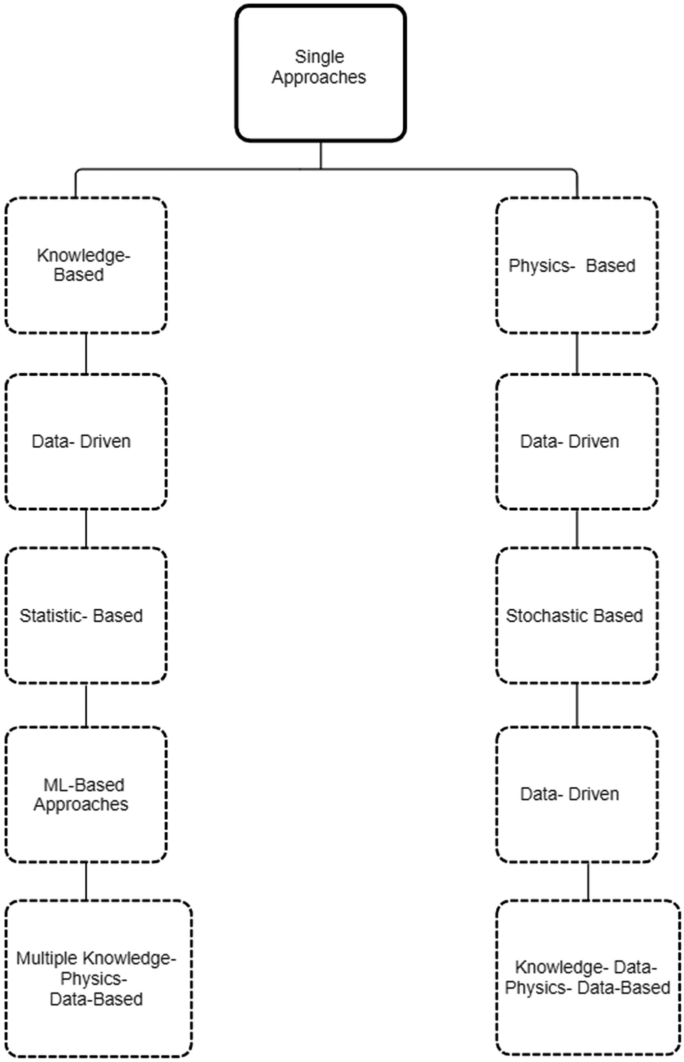


Figure 1.6 Simplified branch diagram illustrating the improvement of predictive maintenance classes in Industry 6.0

1.5.1 Report on predictive maintenance in mining industry: grinding mill case study

Case Study Overview: The case study explores the application of predictive maintenance in the mining industry, specifically focusing on critical assets like grinding mills. Authored by Ayoub Rihi, Salah Baïna, Fatima-zahra Mhada, Essaid Elbachari, Hicham Tagemouati, Mhamed Guerboub,

and Intissar Benzakour, the study addresses the challenges associated with maintaining industrial mining machines and emphasizes the significance of predictive maintenance over traditional approaches [97].

Problem Statement: The maintenance of industrial mining machines, especially critical assets like grinding mills, poses challenges that impact the overall mining process. Traditional maintenance strategies involve either waiting for a failure to occur (curative maintenance) or replacing components regardless of their condition (preventive maintenance). Both approaches result in inefficiencies, leading to equipment loss, downtime, and budgetary waste.

Objective: The study aims to provide a cutting-edge analysis of recent advancements in predictive maintenance, harnessing machine learning algorithms, including deep learning. Its primary goal is to amalgamate diverse case studies employing predictive maintenance techniques and to propose a data-driven model specifically tailored for mining industry assets, with a particular emphasis on grinding mills.

Approach and Methodology: The authors employ machine learning algorithms, including deep learning, to develop a predictive maintenance model. They review recent works in the field, analyzing the strengths and weaknesses of different approaches. The study emphasizes the importance of considering the condition of equipment to optimize maintenance efforts, reduce downtime, and enhance cost-effectiveness.

Key Findings: The case study highlights the inadequacies of curative and preventive maintenance in the mining industry, paving the way for predictive maintenance as a more efficient alternative. By leveraging machine learning algorithms, the authors propose a data-driven model tailored for mining assets, with a specific focus on grinding mills. The findings suggest that predictive maintenance, informed by real-time data and condition monitoring, can significantly improve the reliability and efficiency of critical mining equipment.

Significance and Implications: The adoption of predictive maintenance in the mining industry, as outlined in the study, has the potential to revolutionize asset management practices. By utilizing advanced algorithms, mining companies can optimize maintenance schedules, minimize downtime, and allocate resources more effectively. The proposed data-driven model offers a tailored approach, emphasizing the exceptional requirements of the mining sector, particularly in the context of critical assets like grinding mills.

Conclusion on Case Analysis: In conclusion, the case study delivers valuable insights into the application of predictive maintenance in the mining industry, with a specific focus on grinding mills. The authors advocate for a paradigm shift from traditional maintenance approaches to a data-driven model, highlighting the role of ML (machine learning) algorithms in improving the overall efficiency of mining operations.

1.5.2 Report on sensor-based predictive maintenance with reduction of false alarms

Case Study Overview: Sensor-Based Predictive Maintenance with Reduction of False Alarms – Case Study in Heavy Industry [98]

Problem Statement: The case study addresses the challenge of identifying undesirable events in heavy industry settings, specifically focusing on instances poorly represented in historical data. This is relevant in scenarios such as crushers at a coal-fired power plant and gantries in a steelworks converter. The primary concern is the need for a predictive maintenance system that operates effectively in cold start conditions without overwhelming machine operators with false alarms.

Objective: To propose and implement a predictive maintenance method based on outlier identification applied to temperature measurements, vibration and other data collected by wireless sensors. The key goal is to reduce false positive alarms, enhance system adaptability to analyzed data, promote interaction with dispatchers, and leverage eXplainable Artificial Intelligence (XAI) methods.

Approach and Methodology: The proposed solution involves transforming collected data into multidimensional feature vectors and applying outlier identification methods. A unique aspect of the approach lies in the development of a methodology for reducing false positive alarms. This methodology encompasses system adaptation to analyzed data, dispatcher interaction, and the utilization of XAI. The experiments conducted on multiple datasets demonstrated a significant reduction in false alarms, with an average of 90.25% improvement compared to stand-alone outlier detection methods.

Key Findings

- The outlier identification method, combined with the proposed reduction methodology, effectively minimized false alarms in heavy industry settings.
- System adaptability to varying data and interaction with dispatchers contributed to the success of the predictive maintenance approach.
- XAI methods played a crucial role in providing transparency and interpretability to the predictive maintenance system.

Significance and Implications: The developed predictive maintenance method holds significance for industrial facilities facing a cold start problem. By reducing false alarms by over 90%, the system becomes more user-friendly, preventing discouragement and disregard. The incorporation of XAI ensures transparency, fostering user trust in the system. This research contributes valuable insights to the field of predictive maintenance, particularly in contexts where historical data inadequately represents undesirable events.

Conclusion on case analysis: The study successfully addresses the challenge of identifying undesirable events in heavy industry through the design and execution of a sensor-based predictive maintenance method. By leveraging outlier identification, multidimensional timeseries analysis, and XAI, the proposed solution demonstrates a substantial reduction in false positive alarms. The methodology's adaptability to various data sets and its real-world implementation highlight the practicality and effectiveness of the approach. This research opens avenues for further advancements in predictive maintenance systems, emphasizing the importance of reducing false alarms to enhance user acceptance and system reliability in industrial settings.

1.6 CONCLUSION

This chapter sheds light on the dynamic interaction of the IIoT, AI, and data analytics in Industry 6.0. Navigating the complexity of today's industrial landscape, it is clear that these changing technologies are not simply smooth entities, but rather interconnected components that drive innovation and efficiency. Through our research, we have witnessed how the convergence of IIoT, AI and data analytics is revolutionizing traditional industrial processes and ushering in a modern era of intelligence, connectivity, and real-time data-driven decision-making. From real-time decision-making, monitoring and predictive maintenance to autonomous optimization and adaptive learning, the possibilities unleashed by this triad are vast and promising. In addition, our review of practical applications and case studies highlighted the tangible benefits and successes achieved by combining these technologies across industries. From manufacturing and energy to healthcare and logistics, organizations use these synergies to streamline operations, improve productivity and deliver added value to customers. However, amid the excitement and potential, it is critical to recognize and respond to the challenges that this technological approach creates. Issues such as cyber security vulnerabilities, ethical considerations and the need to upscale the workforce come up. As we move towards Industry 6.0, it is necessary to prioritize these issues and take proactive measures to overcome risks and ensure responsible and sustainable adoption of these technologies. Essentially, this chapter is a signpost to guide us through the evolving landscape of industrial change. By leveraging the collaborative capabilities of IIoT, AI, and data analytics, industries can reveal opportunities, drive creativity, and thrive in the digital age. As we embark on this journey of exploration and discovery, let us be alert, adaptable, and aware of the ethical implications, ensuring that our progress serves the greater good and contributes to a more prosperous and just future.

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Chapter 2

Artificial intelligence and machine learning in Industry 6.0

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2.1 INTRODUCTION

Artificial intelligence is a part of machine learning (ML) in the fast-expanding universe of industrial technology; each epoch marks a significant milestone in the integration of innovative tools and techniques. As we consider the future of industry, the notion of "Industry 6.0" arises as a conceptual framework that depicts the next stage in this development, spurred by the creations in the fields of ML and AI.

Foundations set by past industrial revolutions, Industry 6.0 represents a paradigm shift toward new levels of automation, intelligence, and adaptability within industrial processes. At its core, Industry 6.0 embodies the convergence of digital technology, data-driven insights, and autonomous systems, transforming traditional manufacturing, supply chain management, and beyond [1, 2].

In this era, AI and ML serve as the linchpins of innovation, helping industries to harness the potential of data in ways previously imagined. From predictive maintenance and individualized manufacturing to streamlined supply chains and AI-driven innovation, these technologies push the bounds of what is attainable, unlocking new paths for efficiency, personalization, and sustainability. Yet, despite the possibilities of Industry 6.0, there are also hurdles to overcome, including ethical considerations, labor reskilling, and assuring fair access to the advantages of technology breakthroughs. As we embark on this journey toward Industry 6.0, it becomes vital to not only embrace the revolutionary potential of AI and ML but also approach their deployment with foresight, accountability, and a dedication to crafting a future that is both successful and inclusive [3].

Artificial intelligence and machine learning are crucial drivers of transforming industries across the globe. In the changing landscape of modern industry, the integration of AI and ML technologies is driving a revolutionary wave, moving us toward what some view as Industry 6.0. This conceptual period symbolizes a combination of cutting-edge technologies with industrial processes, signifying a huge leap forward in automation, optimization, and innovation. At the heart of 6.0 lies the merging of AI and ML

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with traditional industrial domains, accepting a new era characterized by intelligent systems, data-driven decision-making, and adaptive manufacturing. Unlike past industrial revolutions which focused mostly on automation and mass production, Industry 6.0 is defined by its emphasis on harnessing advanced algorithms and computer intelligence to enhance every part of industrial operations.

The applications of AI and ML in Industry 6.0 is gigantic and diverse. From predictive maintenance and quality control to supply chain optimization and demand forecasting, these technologies empower organizations to extract actionable insights from large troves of data, enabling them to operate more efficiently, flexibly, and responsively to market dynamics.

Furthermore, AI and ML enable the new production of highly Product and Services that might be customized and tailored to fit the specific preferences, and demands of individual consumers. Through intelligent automation and adaptive manufacturing processes, enterprises may optimize production workflows, decrease waste, and deliver items with unparalleled levels of precision and quality. However, the deployment of AI and ML in industry also has obstacles and considerations. Combining various technologies in generative AI including cloud computing and Industry 6.0 for website and web development will be part of generating super artificial intelligence.

Issues such as data security and privacy, algorithmic prejudice, and the ethical implications of automation necessitate careful attention and appropriate stewardship. Moreover, the integration of these technologies needs a coordinated effort to upskill the workforce and promote a culture of digital literacy and innovation. As we stand on the cusp of Industry 6.0, the opportunities and possibilities given by AI and ML in industry are endless. By embracing these transformational technologies with foresight and strategic intent, industries can unleash new horizons of productivity, competitiveness, and sustainability, defining a future where innovation thrives and wealth is shared by anyone.

2.2 SIGNIFICANCE OF AI IN INDUSTRY

2.2.1 Overview of industry

Industry 6.0, commonly acknowledged as the sixth industrial revolution, Artificial intelligence (AI) is altering sectors at an ever-increasing pace. AI is being utilized to automate operations, boost productivity, and acquire new insights from data. AI, specifically machine learning, analyzes industrial data to find inefficiencies and optimize manufacturing processes.

Figure 2.1 shows how artificial intelligence (AI) is transforming industries across the board. In all sectors, we need AI with a diverse set of applications that improve efficiency, production, and innovation. Predictive

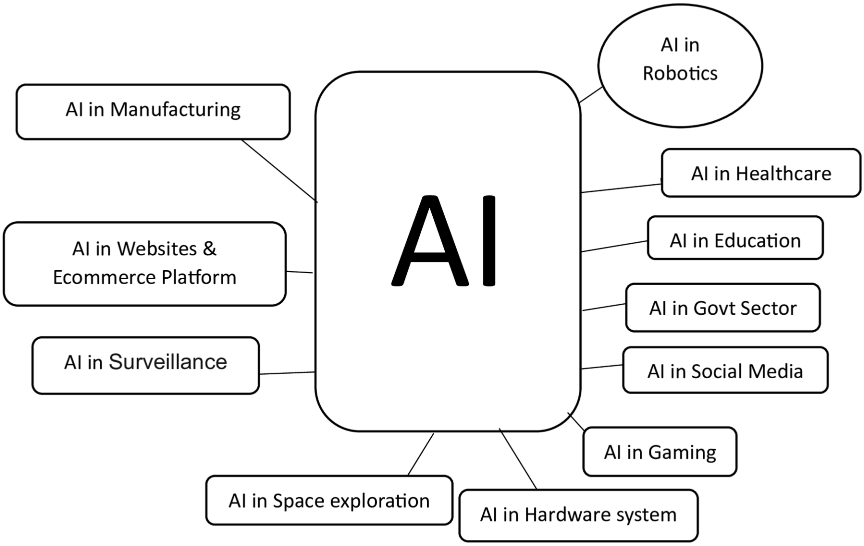

Figure 2.1 Applications of artificial intelligence in various sectors

maintenance: AI algorithms evaluate equipment data to forecast machinery malfunction, thus allowing for preventive maintenance and reducing downtime.

Quality Control: AI-powered computer vision systems can accurately spot flaws in manufactured products, ensuring constant quality. AI-driven analytics improves production processes by finding bottlenecks, decreasing waste, and increasing overall efficiency.

Medical Imaging Analysis: Artificial intelligence algorithms analyze pictures taken during medical tests such as computed tomography (CT) scanning and magnetic resonance imaging (MRI) and help radiologists diagnose diseases and ailments. Personalized treatment: Artificial intelligence analyzes patient data to create treatment programs that are tailored to individual characteristics, enhancing outcomes and lowering adverse effects.

By sifting through massive databases to find potential drug candidates and estimate their efficacy, artificial intelligence (AI) expedites the drug development process.

Fraud Detection: To help financial institutions prevent fraud, artificial intelligence algorithms analyzed transaction data to spot unusual patterns that point to fraudulent activity.

Algorithmic Trading: AI-based and AI-powered trading uses algorithms to examine market data in real time to make quick trading decisions while optimizing investment strategies. For representatives and executives with customer service AI-powered chatbots and virtual assistants offer tailored customer support by answering questions and assisting with transactions.

Personalized suggestions: AI systems evaluate user data to make personalized product recommendations, which improves the shopping experience and increases sales.AI forecasts demand and optimizes inventory levels, lowering stockouts and excess inventory expenditures.AI anticipates renewable energy generation from sources such as wind and solar, allowing utilities to better integrate renewables into their grids [4].

Artificial intelligence (AI) applications span an extensive variety of techniques and methods aimed at enabling robots to accomplish tasks that traditionally require human intelligence. These applications include NLP, or natural language processing, and computer vision to machine learning (ML) and robotics. NLP facilitates the interpretation and creation of human language, enabling virtual assistants, sentiment analysis, and translation services. Computer vision enables robots to understand and analyze visual information, driving improvements in autonomous cars, facial recognition systems, and medical imaging. ML algorithms, including supervised, unsupervised, and reinforcement learning, underpin different AI applications by enabling systems to learn from data and make predictions or judgments. Robotics merges AI with mechanical systems, leading to breakthroughs in industrial automation, healthcare support, and exploration in environments inaccessible to people. Additionally, AI finds applications in domains such as finance, gaming, cybersecurity, or personalized recommendation systems, transforming businesses and reshaping the way we live, work, and interact with computers [5].

AI can advise reductions in cycle times, energy consumption, and material utilization, which can lead to significant cost savings. AI can be used to forecast. This has firms to arrange maintenance before faults occur, which can assist to reduce costly downtime. AI can be used to inspect products for faults. This can help to improve product quality and reduce waste.AI may be used to optimize supply chains by anticipating demand and optimizing inventory levels.AI can be utilized to power chatbots that can answer customer questions and address issues.AI is being utilized to speed the drug development process by finding new therapeutic targets and creating new medications [6, 7].

AI is being used to detect fraud, personalize financial goods, and automate tasks. The influence of AI on industry is still developing, but it is evident that AI has the potential to alter the way we operate. As AI technology continues to evolve, we should expect to see even more imaginative applications of AI in industry [8, 9].

The sixth stage of industry evolution is Industry 6.0, or the Intelligent Revolution, which is expected to occur by the year 2050. It is distinguished by the transition from human–machine collaboration to machine–machine collaboration employing artificial intelligence (AI), quantum computing, blockchain, nanotechnology, biotechnology, and neurotechnology. It also introduces new paradigms such as ubiquitous computing, customer-driven

production, human-centric automation, anti-fragile systems, and intelligent manufacturing.

Industry 6.0 intends to establish a fully integrated, intelligent production system that can function with minimal human intervention. It also aims to create a more resilient and adaptive society where machines can learn from each other and from the environment, where customers can co-create their products and services using digital platforms, where humans can enhance their cognitive and physical abilities using brain–computer interfaces, and where production can be decentralized and distributed using blockchain technology. Quantum computers: These are computers that use quantum mechanics to do calculations that are impossible or impractical for classical computers. They can address complex problems including optimization, encryption, simulation, machine learning, and artificial intelligence. For example, Google has claimed to achieve quantum supremacy by doing a calculation in 200 seconds that would take a supercomputer 10,000 years.

Blockchain: This is a distributed ledger technology that records transactions in a safe, transparent, and unchangeable way. It can enable decentralized and distributed production, supply chain management, smart contracts, digital identity, and peer-to-peer transactions. For example, Wal-Mart has used blockchain to track food products from farm to table and ensure food safety. Nanotechnology is the science and engineering of controlling matter at the nanoscale (one billionth of a meter). It can enable new materials, technologies, and systems with novel properties and functions. For example, IBM has created nanoscale sensors that can detect chemical and biological substances in the environment [10, 11].

2.3 OUTLINE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

The field of computer science described as artificial intelligence is vast and focuses on creating smart agents – that is, autonomous machines having the ability to reason, learn, and act. Studies on AI have been incredibly successful in offering workable solutions for a broad spectrum of instances of error, from diagnosing disease processes to possessing video games. Artificial Intelligence (AI) is a multidisciplinary field focused on constructing devices and systems that carry out tasks that often call for intelligent humans. Reasoning, problem-solving, perception, learning, understanding a foreign language, and decision-making comprise a few of these activities. Machine Learning (ML) is a branch of AI that comprises algorithms and statistical models enabling computers to execute certain jobs without explicit programming instructions. ML algorithms learn from data, finding patterns and generating predictions or judgments based on data. Supervised learning involves training models on labeled data, where the desired output

is known, while unsupervised learning deals with unlabeled data, uncovering hidden patterns or structures within data. Reinforcement learning teaches agents to interact with an environment, learning to attain certain goals through trial and error. AI and ML have applications in different fields, including healthcare, finance, autonomous cars, natural language processing, computer vision, robotics, and more, revolutionizing industries and driving innovation in technology. However, issues like ethical considerations, bias in data and algorithms, clarity, and scalability remain key areas of research and development within the discipline [12].

Machine learning is a part and collaboration of AI that focuses on the construction of algorithms that can learn from data. Machine learning techniques can be used to construct models that can generate predictions or judgments without being explicitly programmed. Imagine you want to teach your child how to ride a bike. You may try to offer them a set of explicit instructions, such as, "Put your left foot on the pedal, then push down with your right foot. Once you're moving, turn the handlebars to steer." This is a symbolic AI approach. Or you may simply let your child get on the bike and experiment. As they fall and get back up, they will eventually learn how to balance and steer. This is a machine learning approach. In the area of AI, machine learning is like the baby trying on the bike. It learns from data (experience) and improves its performance over time [13].

2.3.1 Different kinds of machine learning

Headed Learning: an algorithm is trained on a labeled data set, which fully knows what is expected in this type of learning. A supervised learning system, for instance, may be trained on a collection of pictures of dogs and cats to recognize new images as being composed of the two species.

Unsupervised Learning: In unsupervised learning, the algorithm is trained on an unlabeled dataset, where the desired output is not known. The program must find patterns in the data on its own. For example, an unsupervised learning method may be used to cluster a collection of customer data into various groups.

Reinforcement Learning: In reinforcement learning, the algorithm learns by interacting with its surroundings. The algorithm receives incentives for outstanding acts and punishments for negative actions, and it uses this input to improve its performance over time. For example, a reinforcement learning algorithm could be used to educate a robot to walk (Figure 2.2).

2.3.2 Alternation to Industry 6.0: Emergence of AI and ML

Industry 6.0 reflects a major transformation in the manufacturing landscape, marked by the extensive integration of artificial intelligence (AI) and machine learning (ML) technologies into industrial processes. This

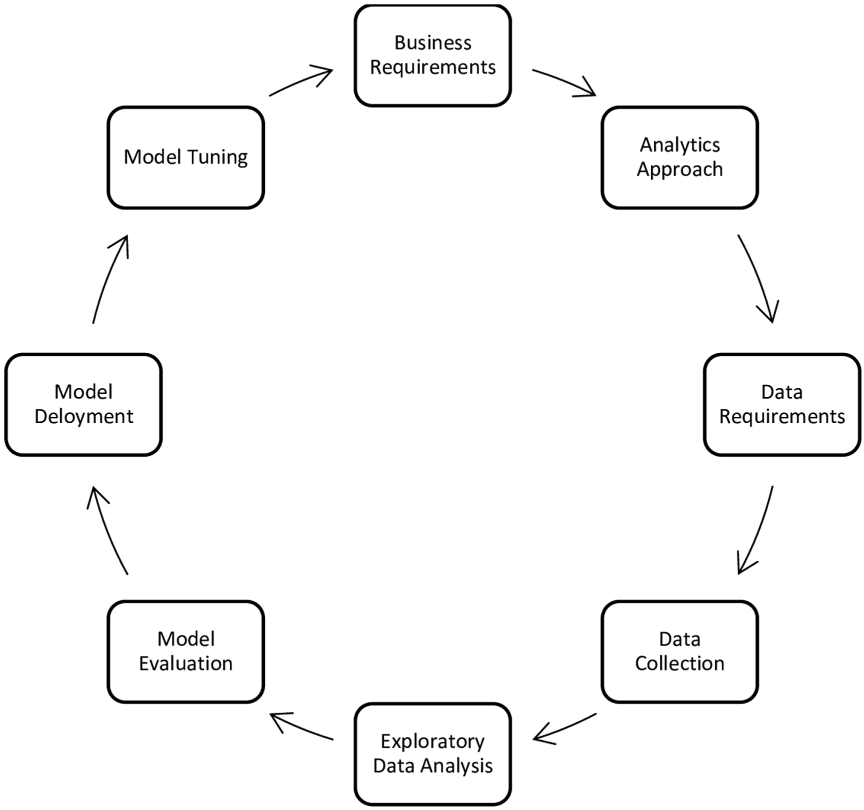

Figure 2.2 Lifecycle of artificial intelligence and machine learning

development is motivated by the demand for greater efficiency, flexibility, and reaction to dynamic market needs. AI and ML play significant roles in enhancing industrial workflows, predictive maintenance, quality control, supply chain management, and resource allocation. Through current data analytics, AI systems can examine huge volumes of sensor data in real-time, detecting trends, anomalies, and prospects for optimization. ML algorithms provide predictive maintenance by forecasting equipment faults before they occur, minimizing downtime and improving output. Additionally, AI-powered robotics and automation improve industrial processes, enhancing precision and decreasing labor costs. As a result, Industry 6.0 fosters a new era of smart, networked factories capable of self-optimization and adaptation to changing conditions, boosting innovation and competitiveness in the global market. However, this transition also brings challenges such as data security, privacy concerns, workforce reskilling, and ethical considerations, necessitating careful planning and collaboration between industry stakeholders, policymakers, and technology providers to ensure a

smooth and responsible integration of AI and ML into industrial operations [14].

AI and ML are causing revolutionary revolutions across industries through diverse applications. Predictive maintenance integrates AI and ML algorithms to forecast equipment issues, lowering downtime and optimizing maintenance schedules. Quality control and assurance benefit from computer vision and ML techniques, ensuring product quality by finding faults and deviations on the production line. Supply chain optimization leverages AI to review data, manage inventory levels, and enhance logistical methods, enhancing efficiency and decreasing costs. Personalized manufacturing employs AI-driven technology to tailor production processes to suit client requests, enhancing product customization and customer delight. Autonomous systems and robots utilize AI to automate activities in manufacturing and logistics, enhancing productivity and safety. Client relationship management employs AI-powered data to adapt client interactions and enhance engagement. Financial forecasting and trading rely on ML algorithms to examine market data and predict trends, impacting investment choices and refining trading strategies. In healthcare, AI and ML boost diagnosis and therapy by reviewing patient data, enhancing accuracy and efficiency in medical decision-making. Energy management and sustainability benefit from AI-driven solutions that optimize energy use, minimize waste, and promote environmental sustainability. Finally, transportation and logistics employ AI for route optimization, demand forecasting, and autonomous vehicle technology, boosting efficiency and minimizing environmental impact across the supply cycle [15, 16].

2.3.3 Revolution of (Industry 1.0 to 5.0) of AI and ML

Industry 1.0: Introduction of Mechanical manufacturing: Industry 1.0 indicates the transition from rural civilizations to industrialized economies, marked by the mechanization of production processes [17].

Key Methods: Water and steam power were vital to this revolution, enabling the establishment of mechanized factories and the mass manufacture of commodities. This period saw the rise of textile mills, iron manufacturing, and the industrialization of agriculture, contributing to great advancements in productivity and economic wealth [18].

Industry 2.0: Mass Production and Electrical Power: Industry 2.0 saw the widespread adoption of electricity and assembly line production techniques, revolutionizing manufacturing processes. Key Methods: Electricity replaced steam power, leading to more efficient and adaptive industrial operations. Assembly lines provided for uniform, high-volume production.

Impact: The automotive industry characterized this age, with Henry Ford's assembly line substantially lowering the cost and time required to build autos. Mass manufacturing became related with economic growth.

Industry 3.0: Automation and Computerization: Industry 3.0 was defined by the emergence of computers and automation technology, ushering in a new era of industrial efficiency and innovation.

Key Methods: Computers, programmable logic controllers (PLCs), and robotics played crucial roles in automating industrial processes and enhancing precision.

Impact: Industries such as automotive, aerospace, and electronics witnessed considerable breakthroughs in automation, resulting in better productivity, quality, and customization possibilities.

Industry 4.0: Digitization and Connectivity: Industry 4.0 anticipates the merging of digital technology with physical systems, yielding "smart factories" capable of networked and autonomous operation.

Key Methods: Internet of Things (IoT), cloud computing, big data analytics, and cyber-physical systems enabled real-time data collecting, analysis, and decision-making.

Impact: Smart manufacturing processes enabled for predictive maintenance, real-time optimization, and customization at scale. The concept of "Industry 4.0" highlighted the integration of digital technology across the complete value chain.

Industry 5.0: Human-Centric Automation: Industry 5.0 encourages collaboration between humans and technology, leveraging AI, ML, and advanced robotics to supplement human talents rather than replace them.

Key Methods: AI, ML, collaborative robots (cobots), and augmented reality (AR) allow safer and more natural human–machine contact.

Impact: Industry 5.0 tries to address challenges such as worker displacement and skill shortages by building a symbiotic alliance between humans and technology. It stimulates creativity, problem-solving, and adaptation in the workplace, paving the route for a more strong and inclusive industrial future.

2.4 PRINCIPLES OF AI AND CONCEPTS OF MACHINE LEARNING

The principles of artificial intelligence (AI) concentrate upon developing systems or robots capable of accomplishing actions that typically need human intelligence. This encompasses several concepts and methodologies, with machine learning (ML) being a fundamental component.

Machine Learning: ML is a subset of AI that focuses on developing algorithms and models that enable computers to learn from data. These algorithms boost their performance over time as they are exposed to more data, without being explicitly coded. ML encompasses several techniques, including supervised learning, unsupervised learning, and reinforcement learning.

Supervised Learning: In supervised learning, models are trained using a labeled dataset, where each input is associated with a matching output. The

algorithm learns to transfer input data to the correct output by reducing the distance between its predictions and the true labels. Common applications include classification and regression tasks.

Unsupervised Learning: Unsupervised learning involves training models on unlabeled data, where the algorithm must detect patterns or structures within the data without direction. Clustering and dimensionality reduction are common challenges in unsupervised learning, helpful for tasks such as customer segmentation or anomaly detection.

Reinforcement Learning: Reinforcement learning is a paradigm where an agent learns to interact with an environment in order to maximize some notion of cumulative reward.

Through trial and error, the agent learns which behaviors yield the most favorable effects. Reinforcement learning is generally applied in scenarios when explicit input is little or delayed, such as game playing, robotics, and autonomous vehicle control.

Neural Networks and Deep Learning: Neural networks are a class of algorithms inspired by the structure and function of the human brain. Deep learning, a field of ML, entails training neural networks with numerous layers (deep architectures) to learn hierarchical representations of input. Deep learning has led to substantial breakthroughs in disciplines such as computer vision, natural language processing, and speech recognition.

Feature Engineering: Feature engineering is the process of choosing, altering, and producing features (input variables) to improve the performance of machine learning algorithms. Effective feature engineering can drastically increase the performance of ML models, usually requiring topic expertise and imagination.

Model Evaluation and Validation: Evaluating and validating ML models is crucial to evaluate their effectiveness and generalization to unseen data. Techniques such as cross-validation, train-test splitting, and performance metrics (e.g., accuracy, precision, recall, F1-score) are used to examine model performance and detect potential problems such as overfitting or underfitting.

Ethical Concerns: As AI and ML technologies become increasingly popular, ethical questions concerning justice, responsibility, transparency, and privacy are critical. Addressing biases in data and algorithms, ensuring transparency and interpretability of models, and protecting privacy rights are crucial for responsible AI adoption.

Cognitive computing includes designing computers that emulate human thought processes. These systems are designed to evaluate, reason, and learn from data in a manner analogous to people and computer vision focuses on allowing machines to perceive and understand visual information from the surrounding environment. Both cognitive computing and computer vision play essential roles in many AI applications, including autonomous cars, medical imaging, robotics, surveillance systems, and human–computer

interaction. These domains continue to expand fast, driven by continuous research, technology advancements, and real-world applications.

2.4.1 Current instances of AI and ML use in diverse industries

Artificial intelligence (AI) and machine learning (ML) are altering numerous industries, enhancing efficiency, decision-making, and customer experiences. Here are some real-world cases of AI and ML implementation across varied sectors:

AI in Healthcare: AI algorithms are used to analyze medical pictures such as X-rays, MRIs, and CT scans to assist radiologists in detecting abnormalities and diagnosing diseases more correctly. ML models examine huge datasets to find possible drug candidates, predict their efficacy, and optimize drug development processes, leading to quicker and more cost-effective drug discovery [19, 20]. AI-based algorithms examine patient data, including genetic information, medical history, and lifestyle factors, to design treatment programs and forecast individual responses to medications.

Fraud Detection: ML algorithms study transactional data to discover patterns suggestive of fraudulent conduct, letting financial institutions identify and prevent fraudulent transactions in real-time. AI-powered trading systems apply ML models to assess market data, locate trading opportunities, and execute trades automatically, boosting investing methods and lowering human error. ML algorithms analyze individuals' creditworthiness by considering multiple data points, including credit history, income, and spending patterns, enabling lenders to make more accurate loan choices [21, 22] (Figure 2.3).

2.5 UPCOMING INNOVATIONS RELATED TO THE FUTURE OF INDUSTRY 6.0 AND PREDICTIONS FOR THE GROWTH OF AI AND ML IN INDUSTRY

Emerging technologies such as artificial intelligence (AI) and machine learning (ML) are poised to drastically affect the environment of Industry 6.0. Predictions for their evolution include a continual integration into different sectors, rising automation, optimization, and innovation. AI and ML algorithms will develop more complex, delivering deeper insights from large datasets and facilitating predictive analytics for enhanced decision-making. Industry 6.0 will witness the rise of AI-driven autonomous technologies, from smart factories to self-driving vehicles, streamlining operations and improving productivity. Furthermore, AI and ML will promote the development of personalized products and services, suited to individual preferences through improved data analysis. Collaborative robots or robots will

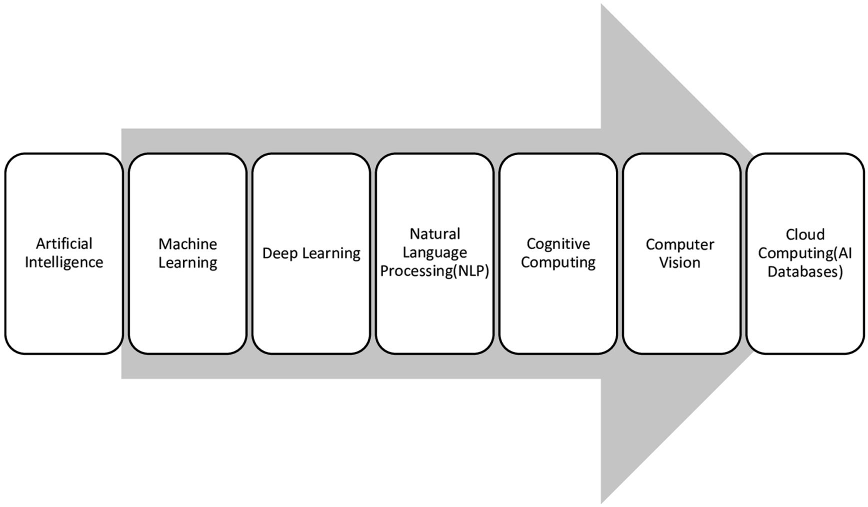

Figure 2.3 AI/ML in Industry 6.0

become increasingly widespread, working alongside people in a synergistic manner, enhancing productivity and safety in industrial settings [23]. Moreover, explainable AI will gain popularity, ensuring transparency and accountability in algorithmic decision-making processes. As Industry 6.0 evolves, AI and ML will continue to be essential elements in driving innovation, competitiveness, and sustainable growth.

2.5.1 Challenges and opportunities in Industry 6.0

As automation grows, certain tasks previously performed by people could be supplanted by robots. However, new possibilities will exist in sectors like AI research, machine maintenance, and data analysis. Improving the skills of the workforce will be important for a seamless transition.

In Industrial 6.0, the amalgamation of artificial intelligence (AI) and space exploration promises a cornucopia of potential. AI can revolutionize space technology, providing autonomous navigation, data processing, and mission planning, hence minimizing human interference, and working expenditures. One huge prospect comes in the application of artificial intelligence for satellite communication and navigation systems, enhancing the reliability and efficiency of space-based infrastructure. In addition, AI-powered robots can aid duties like satellite servicing, assembly, and repair, prolonging the lifespan of present assets and enabling the building of large-scale space homes or structures. Furthermore, AI systems can examine vast amounts of space data, including photographs, telemetry, and sensor readings, to find novel celestial occurrences, suggest prospective landing

spots for research missions, and forecast space weather patterns. Moreover, AI can maximize the use of resources in space missions, from monitoring fuel consumption to recycling waste and upholding long-duration human spaceflight. Embracing these prospects in AI-driven space exploration may hasten scientific discovery, enabling sustainable space flight, and pave the way for the colonization of other celestial bodies, ushering in a new age of human presence beyond the planet's gravity [24].

AI and ML application has grown increasingly popular across numerous sectors, altering processes, and revealing new possibilities. In medical care, IBM's Watson Health uses AI to analyze health data and aid clinicians in identifying ailments and providing customized therapy regimens [25]. Retail giants like Amazon deploy ML algorithms to power recommendation systems, enhancing consumer experiences and increasing sales. Financial institutions utilize AI for fraud detection and risk management, with businesses like PayPal utilizing ML to analyze transaction patterns and detect fraudulent actions in real-time. In manufacturing, predictive maintenance enabled by AI helps firms like General Electric anticipate equipment breakdowns, saving downtime and improving maintenance schedules. Autonomous cars, such as those created by Tesla, utilize AI for navigation, vision, and decision-making, paving the way for the future of transportation. Moreover, in agriculture, firms like John Deere apply ML algorithms to evaluate information collected by sensors and drones, optimizing crop yields and resource efficiency. These real-world examples highlight the disruptive impact of AI and ML across a variety of industries, boosting innovation, efficiency, and profitability [26].

2.5.2 Modeling for Industry 6.0 in AI

Industry 6.0 represents the next evolution of industrial practices, integrating advanced technologies such as artificial intelligence (AI), Internet of Things (IoT), robotics, and advanced data analytics to further enhance efficiency, productivity, and innovation in manufacturing and other industries. Developing AI models to optimize supply chain operations by evaluating massive volumes of data from numerous sources, including suppliers, logistics partners, and consumer demand projections. These models can aid in inventory management, route optimization, and demand forecasting, leading to decreased costs and increased employment of AI-powered robots and automation systems to conduct repetitive jobs with great precision and efficiency. Models may be taught using techniques such as reinforcement learning to enable robots to adapt to changing surroundings and tasks independently. : Designing AI solutions that promote seamless collaboration between humans and robots in the industrial setting. Models can be designed to increase human–machine interaction, such as natural language processing for voice-activated controls or augmented reality interfaces for

intuitive assistance in complicated tasks. Integrating AI-powered cybersecurity methods to safeguard sensitive industrial data and systems from cyber-attacks. AI models may evaluate network traffic patterns and user activities to detect and prevent security breaches, while also assuring compliance with data protection rules (Figure 2.4).

In Industry 6.0, the AI ecosystem encompasses numerous important components that jointly promote innovation and growth across multiple industries. Advanced algorithms and models are at the heart, permitting computers to learn, anticipate, and optimize autonomously employing approaches such as deep learning and reinforcement learning. Supporting this is a sophisticated big data infrastructure, supporting the storing, processing, and analysis of massive volumes of data created by industrial processes and IoT devices. IoT devices serve as the sensory network, capturing real-time data from machinery and equipment, while edge computing pushes computation closer to data sources for real-time processing. Robotics and automation technologies enable the deployment of AI-powered robots for activities ranging from assembly to inspection, boosting efficiency and precision. Digital twins provide virtual reproductions of genuine assets, enabling real-time simulation and optimization [27].

Cybersecurity solutions are vital to preserving sensitive data and infrastructure, employing AI for real-time threat detection and response. Collaborative ecosystems foster knowledge exchange and partnerships, increasing the adoption of AI technology, while ethical and regulatory frameworks assure appropriate deployment and usage, balancing innovation with society values and safety considerations. Together, these components represent the cornerstone of the AI industry in Industry 6.0, facilitating continual innovation and progress across multiple industrial sectors [28].

In Industry 6.0, the combination of Edge computing, quantum computing, cybersecurity, robotics, and big data AI delivers a revolutionary force changing industrial processes and operations. Edge computing plays a key role by moving compute and data storage closer to the data source, enabling real-time processing and analysis of massive volumes of data generated by IoT devices and industrial sensors. This specialized processing capability facilitates speedier decision-making, lowers latency, and boosts the responsiveness of AI-driven systems in dynamic industrial conditions. Quantum computing shows potential for addressing tough optimization and simulation issues at an unprecedented scale, with the possibility to improve AI algorithms and speed breakthroughs in fields such as materials research, medication development, and supply chain optimization. However, with these gains come heightened cybersecurity concerns, as networked industrial systems become increasingly exposed to cyber breaches and assaults.

Robust cybersecurity measures are necessary to preserve sensitive data, intellectual property, and important infrastructure, employing AI-driven solutions for real-time threat detection, vulnerability assessment, and incident response. Robotics plays a significant part in Industry 6.0, with

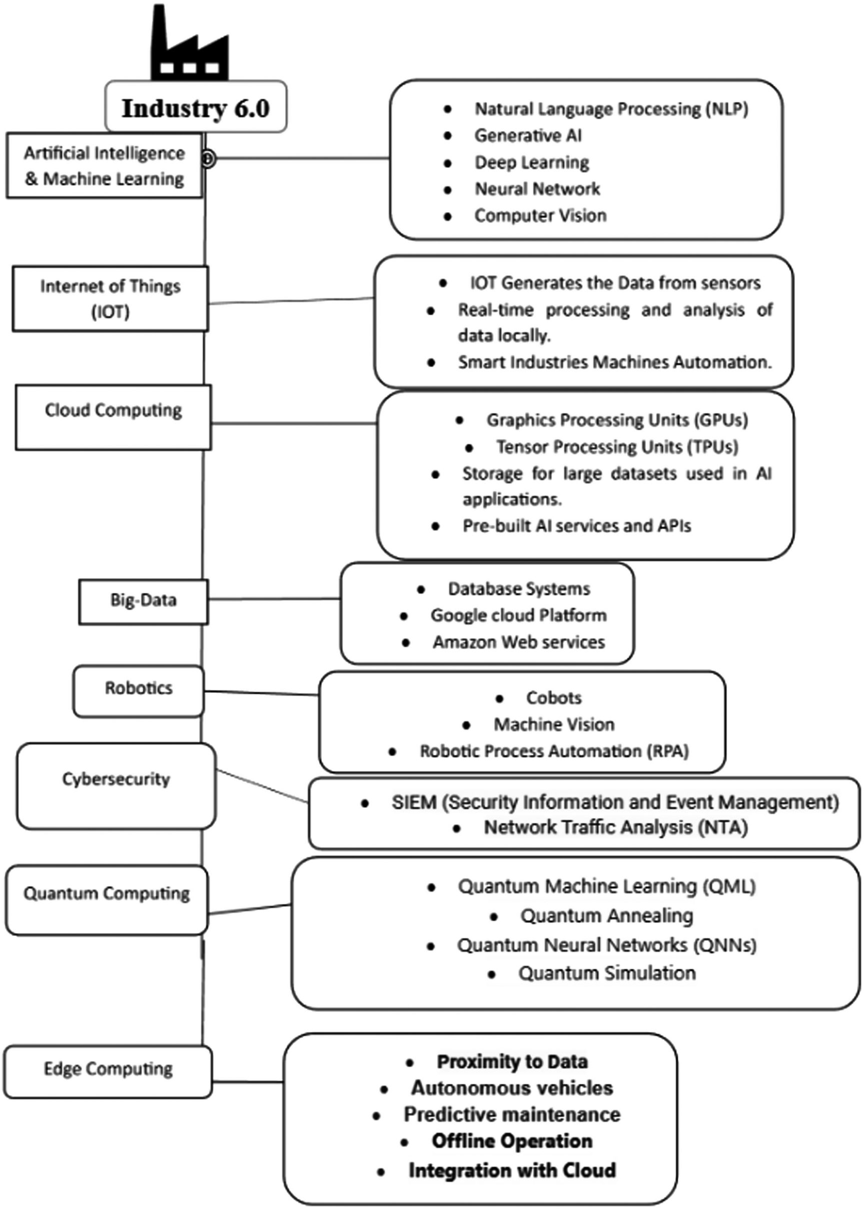

Figure 2.4 Components of AI in Industry 6.0

AI-powered robots conducting a wide range of jobs, from assembly and material handling to inspection and maintenance. These robots interact seamlessly with human workers, boosting efficiency, accuracy, and safety in industrial situations. At the heart of Industry 6.0 lies big data AI, where sophisticated algorithms and machine learning models assess and generate insights from huge datasets to optimize production processes, detect equipment faults, and boost product quality. Together, these technological components drive the evolution of Industry 6.0, unlocking new levels of efficiency, productivity, and innovation across diverse industrial sectors while also posing new challenges that must be addressed to ensure the secure and responsible deployment of AI-driven technologies.

2.6 CONCLUSION

To recapitulate, the introduction of AI and ML technologies into Industry 6.0 ushers in a new era of innovation, efficiency, and competitiveness across several industries. Artificial intelligence and machine learning have the ability to transform industrial processes, increase product quality, and drive predictive maintenance procedures. Industry 6.0 enables real-time decision-making, automation, and optimization by leveraging advanced algorithms, big data analytics, and IoT devices, opening the way for smart factories and self-driving production systems. Furthermore, AI and machine learning are revolutionizing traditional industries such as automotive, healthcare, and aerospace, enabling for advancements in self-driving vehicles, personalized medicine, and predictive aircraft maintenance. Edge computing, quantum computing, and robotics work together to drive innovation by opening up new possibilities for industrial optimization, simulation, and exploration. However, as Industry 6.0 develops, a number of concerns and considerations arise that must be addressed. These include concerns about data privacy, algorithmic unfairness, cybersecurity risks, and employment displacement. Ethical and regulatory frameworks are essential to ensure that AI-driven technology is deployed and used appropriately, while also balancing innovation with societal values and safety concerns. Industry 6.0 holds enormous promise for further growth and progress. Collaborative ecosystems, diversified research, and investments in talent development are required to realize AI and ML's full potential for long-term industrial advancement and economic success. By embracing innovation and adaptability, stakeholders may navigate Industry 6.0's difficulties and create new possibilities for innovation, efficiency, and value production in the global marketplace. AI and machine learning in Industry 6.0 offer an intelligent production future marked by greater automation, real-time optimization, and human–machine cooperation, eventually ushering in a new era of industrial efficiency and manufacturing.

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Chapter 3

Big data fusion with GEN AI Tools

Driving Industry 6.0 advancements

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3.1 INTRODUCTION

Amidst the backdrop of the coronavirus disease 2019 (COVID-19) pandemic, the efficacy of CT scans, powered by image-diagnosing algorithms, emerged as a pivotal tool for swift and accurate virus diagnosis. Leveraging AI and machine learning technologies, these scans proved instrumental in identifying new variants of the virus, facilitating prompt adjustments in medication protocols. This expedited analysis played a pivotal role in steering the global populace towards a return to normalcy post-pandemic.

Indeed, artificial intelligence and machine learning have transcended the confines of specialized fields, pervasive into our daily lives with profound impact. The big data serves as an expansive reservoir of information, encompassing both structured and unstructured data formats. Its sheer magnitude renders manual processing impractical, necessitating the application of advanced computational techniques for meaningful analysis and interpretation. Beyond healthcare, these technologies find applications in diverse domains, ranging from finance and marketing to transportation and entertainment, shaping the fabric of modern society in innumerable ways. In this context, it becomes increasingly apparent that the effective utilization of big data hinges upon the integration of AI and machine learning algorithms, enabling organizations to extract actionable insights and drive informed decision-making. However, as we navigate this era of unprecedented technological advancement, it is imperative to remain cognizant of the ethical considerations and societal implications inherent in the widespread adoption of these technologies. In the subsequent sections of this paper, we will delve into the intricate interplay between big data, artificial intelligence, and machine learning, exploring their transformative potential across various sectors. Through a comprehensive analysis of real-world applications and emerging trends, we aim to provide insights into how organizations can leverage these technologies to navigate the complexities of our rapidly evolving digital landscape while fostering innovation and driving sustainable growth.

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3.2 ARTIFICIAL INTELLIGENCE

Artificial intelligence is intelligence that is demonstrated by machines, especially computers and computer-based machines. AI has a wide range of applications which include advanced web searches, recommendation systems (YouTube and Netflix recommendations), generative tools, etc. [1]. Generative tools which are powered by AI are current sensations – chatbots like ChatGPT and Bard in contemporary technology landscapes [2]. AI works by taking in large amounts of training data then they further form correlations and patterns between all the data that is available to them to make future predictions. One single programming language cannot be synonymous with AI, but Python, C++, and Java have features that are popular among AI developers.

AI primarily focuses on cognitive skills which include the following:

- **Learning**: The job of an AI is to acquire data and create algorithms and provide computing networks with step-by-step instructions on how to complete a certain task.
- **Reasoning**: The AI also needs to use the most suitable algorithm to bring out the desired outcome.
- **Continuous refinement:** AI incorporates self-correction mechanisms to continually adjust algorithms, ensuring they deliver the most precise outcomes.
- **Innovation:** AI utilizes its creative capabilities to generate fresh images, text, music, and ideas.

3.3 MACHINE LEARNING

Machine learning falls under the roof of artificial intelligence (AI) which can be defined as the ability of a machine to learn human behavior. The machine learning models are trained with labeled data sets, which then develop abilities to grow more accurately [3]. Machine learning has applications in fields like image recognition, automotive language, medical diagnosis, speech recognition, traffic prediction, etc. Supervised, Unsupervised, Semi-Supervised, and Reinforcement learning are the different types of machine learning.

1. **Supervised:** The main process of the supervised is to plot the input variable to the output variable. This model is trained using a labeled data set and then processed using a test dataset. It is widely used in medical imaging and spam filtering.
2. **Unsupervised:** The unsupervised model is fed with unsorted data and the output is predicted according to the pattern, similarities, and

differences. Some of the cons of using this type are that the output may be less accurate, as it is not trained with supervised algorithms.

3. **Semi-supervised:** As we know by the name it lies between the process of supervised and unsupervised models. It has few labels (for marketable purposes), which are relatively costlier than unlabeled data. It was mainly created to solve the drawbacks of supervised and unsupervised learning algorithms.
4. **Reinforcement language:** This AI model automatically updates its responses according to the feedback given. It explores its surroundings by the hit-and-trial method.

3.4 ROLE OF BIG DATA IN MACHINE LEARNING

The words big data and Machine learning are often used together. What is the relationship between these two terms? Machine learning requires vast amounts of data to function at the efficiency it works in the present. Big data fuels machine learning to enhance its decision-making processes and improve its efficiency [4]. It also helps in the escalation of the analytics done by Machine Learning. When big data and machine learning come together the users can be empowered with intuitive tools and robust technologies. With the help of these tools, users can extract high-value information from a given set of data. This leads to the fostering of data literacy amongst the members of an organization [5, 6].

The different ways big data and machine learning are utilized by organizations are as follows:

- All these analyses can help predict certain market trends and organizations can capitalize on these trends, leading to an economic boom.
- We can trace consumer behavior and interests which will help various organizations cater to the needs of consumers [7].
- Digital marketing campaigns can be optimized and personalized to one's needs. This will help the campaigns of organizations stand out from one another attracting different target audiences [8].
- Machine learning helps in linking big sets of data and provides deep insights through the analyses. These insights can be utilized for improved decision-making [9].

3.5 CHATGPT

ChatGPT, an artificial intelligent language model also known as Chat Generative Pretrained Transformer, is capable of producing natural, human-friendly language. This language model (ChatGPT) serves a variety

of industries, including customer service, content development, language translation, entertainment, and education. It also works as a personal assistant and mental health supporter. ChatGPT was developed by Open AI in November 2022 [10, 11].

3.5.1 Open AI

OpenAI is a research institution that has played a crucial role in advancing Artificial General Intelligence (AGI), notably through pioneering developments such as the GPT (Generative Pretrained Transformer) language models, the DALL-E image generation model, and the robotics system known as Dactyl. In addition to research, Open AI also collaborates with industries and governments to ensure that AI is developed in a safe and ethical manner [12]. This company has received several funding from notable investors which include Microsoft, Reid Hoffmann, Peter Thiel, and Khosla Ventures. In addition to developing AI applications, Open AI also works on policies and educational initiatives

3.5.2 Architecture of ChatGPT

Natural-language processing operations like sentimental analysis and question answering are built into the ChatGPT architecture. This Transformer architecture, a kind of neural network made for processing sequential data, including text written in natural language, is the foundation of this design. Transformer encoder layers are stacked in this architecture to capture the relationships between words in the input text. Also, it contains several methods to enhance the model's performance and stability [13]. The model is additionally pre-trained using an enormous collection of text data.

It relies on NLP (Natural Language Processing) which is an excellent tool for experimenters and inventors working on creative NLP systems, and it has numerous specific tasks, disciplines, and operations available to work within it. It is well-trained on prejudiced and unprejudiced data, in the form of textbooks, papers, and websites [14]. Still, it is prone to make mistakes, depending on its training data.

One of the most significant operations of ChatGPT is natural language understanding (NLU). Figure 3.1 illustrates the process between the user and ChatGPT. This is the process of extracting meaning from natural language texts, and it is a pivotal element of numerous AI operations, including chatbots and automated client service systems. ChatGPT 's capability to understand and respond to natural language prompts makes it an ideal tool for NLU, and it is formerly being used by numerous businesses and associations to ameliorate their client service and engagement [15]. Figure 3.2 shows the relationship between NLP and NLU. In addition to its use in NLU, ChatGPT is also being used in a wide range of other operations,

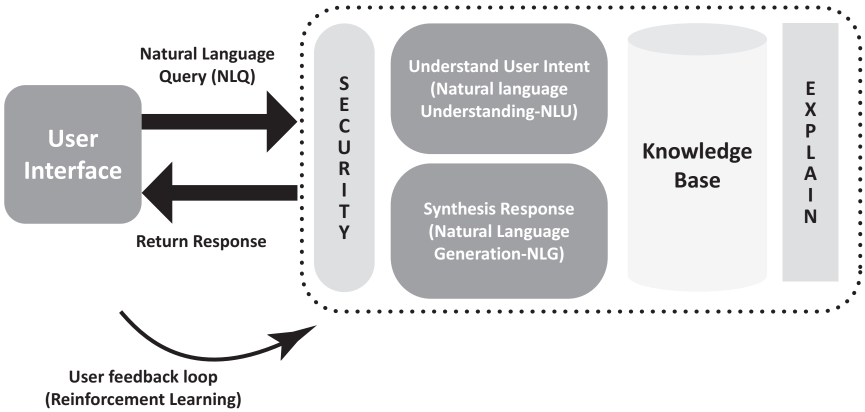


Figure 3.1 The process between the user and ChatGPT

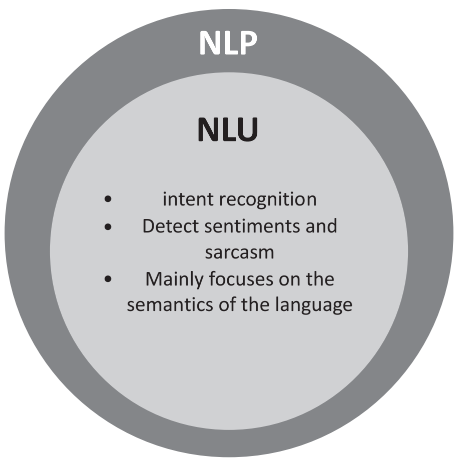


Figure 3.2 Relationship between NLP and NLU

including content creation and language restatement. Its capability to induce high-quality texts that are environment dependent makes it a precious tool in numerous areas of digital frugality [16].

ChatGPT is trained on GPT-3.5 architecture, developed by Open AI. As of now, the chatbot is trained on GPT-4. Both versions belong to the large language models (LLMs) that use both supervised and reinforcement learning [17]. This cutting-edge natural language processing system has undergone extensive training on vast datasets, empowering it to produce top-tier textual responses across diverse prompts. GPT-3 harnesses 175 billion parameters, constituting a massive dataset and a sophisticated network of computers to create a comprehensive language model (LLM) [18].

Table 3.1 Difference between the parameters of the evolving GPTs

	GPT-1	*GPT-2*	*GPT-3*
Parameters	117 million	1.5 billion	175 billion
Decoded Layers	12	48	96
Hidden layers	768	1600	12288
Context Token Size	512	1024	2048

Table 3.1 shows the comparison between GPT-1, GPT-2, and GPT-3. The newly released GPT-4 has a much larger load of data.

3.5.3 Objective of ChatGPT

The core aim of ChatGPT is to provide users with a seamless means of engaging with machines through natural language. This goal is realized through extensive training of the model on diverse textual sources such as books, papers, and various human-written contents, enabling it to grasp patterns and correlations among different words and phrases [19]. After training, the model is capable of generating contextually relevant texts and comprehending intricate queries and commands tailored to its environment. ChatGPT's key advantage lies in its ability to interpret and reply to diverse language styles encompassing formal, informal, and conversational tones. This means that users can communicate with the system in a way that feels natural to them, rather than being limited to a particular style or set of commands.

ChatGPT can also handle multiple languages, which makes it a precious tool for businesses and associations that operate in global aspects. Another crucial point of ChatGPT is its ability to learn and adapt over time (deep learning). The system can be continually trained on new data, which allows it to enhance its performance and delicacy over time [20]. This is essential in a world where language is constantly evolving, and innovative words and expressions are being introduced all the time. Its adeptness at comprehending and addressing various language styles, coupled with its potential for ongoing learning and improvement, positions it as a fundamental component within numerous AI systems. As natural language processing progresses, ChatGPT is poised to significantly influence the evolution of human-machine communication in the foreseeable future.

3.5.4 Advantages of ChatGPT

Chat GPT is designed to understand human language and induce responses that are natural and coherent [21]. This positions it as an exceptional tool for human communication and knowledge dissemination across various fields. ChatGPT undergoes training on extensive textual datasets, empowering it to grasp and analyze intricate language patterns efficiently.

Consequently, it can promptly deliver more precise and relevant responses to inquiries. Moreover, ChatGPT's versatility extends to its ability to be trained on diverse datasets spanning multiple disciplines, enhancing its overall capabilities. It finds application across a broad spectrum of tasks, including chatbots, customer service, language translation, and beyond. Notably, ChatGPT has the potential to replace human agents in certain customer service operations, leading to significant cost savings for businesses. Furthermore, its scalability allows seamless adjustment to match operational requirements, enabling it to efficiently manage high volumes of requests without compromising performance [22]. Therefore, it is a valuable tool that can give numerous benefits to businesses and individuals.

3.5.5 Capabilities of ChatGPT

This is a language model that is used to answer all our questions, write a letter, draft emails, talk to us like a fellow person, explain a code, write a code, and many more based on the prompts we feed in. ChatGPT can act as a text translator. It can generate poems in a short span of time or even write a whole song. It can explain complex topics in a simpler and understandable manner. It can write, debug and explain a code in seconds. Figures 3.3 and 3.4 show a sample poem generated by ChatGPT and code debugged and generated by ChatGPT respectively.

ChatGPT is a boon and a threat to the future generation. It has the potential to increase productivity and reduce the time span of work, but it also has the potential to eliminate jobs, particularly in low-skilled industries [23]. People might lose the ability to think creatively, and they might completely depend on machines that might promote biased decisions.

3.6 DALL-E

DALL-E, a machine-learning model developed by OpenAI and released in January 2021, generates digital images based on textual descriptions. It

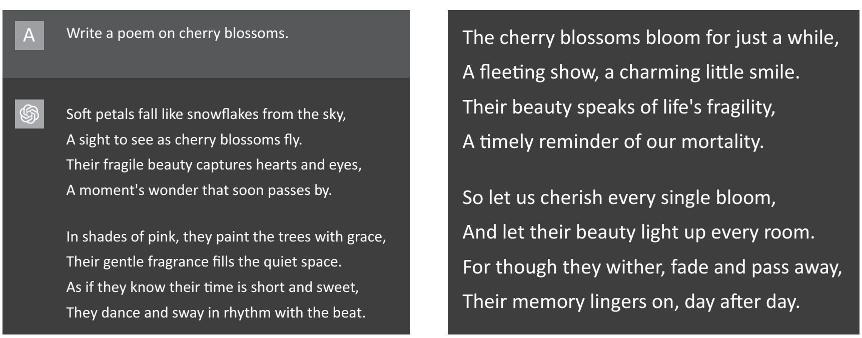
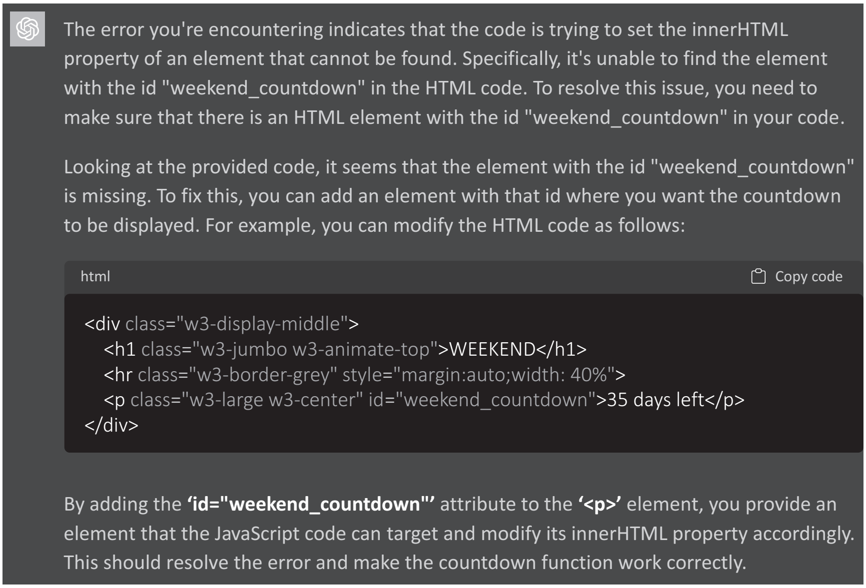


Figure 3.3 A poem generated by Chat GPT



The error you're encountering indicates that the code is trying to set the innerHTML property of an element that cannot be found. Specifically, it's unable to find the element with the id "weekend_countdown" in the HTML code. To resolve this issue, you need to make sure that there is an HTML element with the id "weekend_countdown" in your code.

Looking at the provided code, it seems that the element with the id "weekend_countdown" is missing. To fix this, you can add an element with that id where you want the countdown to be displayed. For example, you can modify the HTML code as follows:

html Copy code

```html
<div class="w3-display-middle">
  <h1 class="w3-jumbo w3-animate-top">WEEKEND</h1>
  <hr class="w3-border-grey" style="margin:auto;width: 40%">
  <p class="w3-large w3-center" id="weekend_countdown">35 days left</p>
</div>
```

By adding the **‘id="weekend_countdown"’** attribute to the **‘<p>’** element, you provide an element that the JavaScript code can target and modify its innerHTML property accordingly. This should resolve the error and make the countdown function work correctly.

Figure 3.4 Code debugged and generated by ChatGPT

leverages the GPT-3 architecture, also developed by OpenAI in 2018, which utilizes a Transformer architecture. A newer iteration, DALL-E 2, was introduced in April 2022, aiming to produce more realistic, high-resolution images. OpenAI launched DALL-E 2 as an API in November 2022, enabling users to integrate this model into their software applications [24]. DALL-E operates with various implementation modes, utilizing approximately 12 million parameters trained on generating “text-image” pairs. DALL-E 2 employs 3.5 billion parameters for enhanced performance. While DALL-E generates results within a short timeframe (around 60 seconds), the image quality may not be optimal. For optimal results, the model should ideally take between 30 seconds to 1 minute to generate images.

3.6.1 Some ways to use DALL-E or DALL-E 2 in an efficient way

1) Add all the descriptions about the image you want to generate in the prompt. Figures 3.5 and 3.6 show an example of how DALL-E works better when the description is detailed.

   Always write the prompts clearly using the plus symbol to distinguish each and every description. For example: “*Prompt = Thor + Eating Tacos + Angrily + Hammer by the side + In a Taco Bell + Situated in Asgard*”.

Figure 3.5 Undescripted prompt

Figure 3.6 Descripted prompt

Figure 3.7 Camera and lighting angle specified images

2) Other ways to enhance the image are by mentioning the way of art you prefer. Like oil painting, watercolor images.
3) Specify the camera angle and the lighting angle in the picture. Figure 3.7 shows a sample image generated by DALL-E where the specification of the lighting is mentioned in the prompt.

3.6.2 Working principle of DALL-E 2

DALL-E takes in textual messages and gives out images according to the description. It has three layers, through which the information is broken down and analyzed.

As we see in Figure 3.8, the text encoder reads the text and generates text embeddings. It is the representation of a word in vector form. For example, hat = [3.675,5.542,8.564]. These text embeddings are taken as input by the middle model called prior. They further generate image embeddings, which are processed by the decoder to give out a full image [25]. DALL-E uses a neural network for the text and image embedding caller CLIP.

3.6.3 CLIP and its working principle

CLIP stands for Contrastive Language-Image Pretraining. It is a zero-shot, multi-modal model that gives the most precise description of an image, without optimizing for a single task. Zero-shot learning is a way of classifying images that the model is not trained on. The specialty of CLIP is that it is not bound by limitations to recognize specific classes [26]. For example, it can solve tasks and datasets that belong to classes like geo-localization, texture recognition, and facial emotion recognition. Multi-modal supports learning from more than one source. CLIP uses both Natural language processing (NLP) and Computer Vision (CV). It is trained with around 400 million image-text sets (ImageNet, an image-text processor, is trained with 1.2 billion only). The more the data, the better and more diversified are the results.

This model was trained in a very interesting manner. The method is called the Contrastive Pre-training method. Figure 3.9 illustrates the process that takes place inside it.

Few images and corresponding texts are passed through image and text encoders respectively. The first image takes the place of “I1” and the nth image takes the place of “In.” Similarly, the texts sent through the text encoder take their assigned places. As we can see in Figure 3.9, the diagonal elements are the correct match and the off-diagonal elements are an incorrect match. So, the diagonal elements are maximized and the other elements are minimized. Another interesting feature is that these minimized

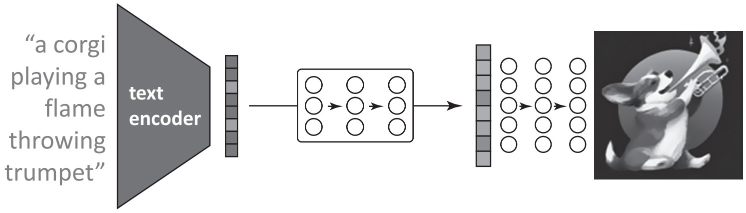


Figure 3.8 Process of text-to-image conversion

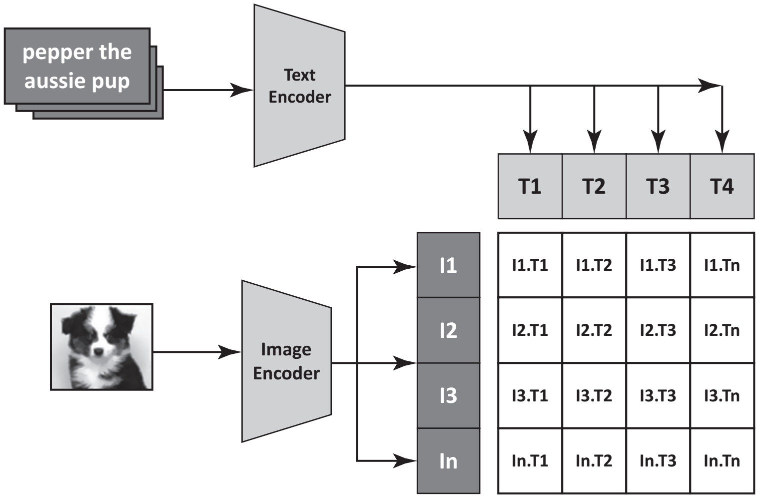


Figure 3.9 Contrastive pre-training

elements are used for image recognition. Along with so many interesting features, it also has a few limitations like it still lags behind on detailed classification like differentiating models of cars, variants of aircraft, etc. It also has trouble generalizing out-of-distribution images, for example, it can detect digitally generated text but has trouble with MNIST (it is a dataset containing handwritten digits). So, as we read about CLIP, it is used in DALL-E 2 for generating text and image embeddings. Now if we take a look at Figure 3.9, we have come to the last stage of generating images from image embeddings. For this process, yet another application was created by Open AI named GLIDE.

GLIDE (Guided Language to Image Diffusion for Generation and Editing) is a Diffusion Model that does a reverse diffusion process where the image is given out as an output from a random noise input. It uses an UN-net-based architecture. The specialty of GLIIDE is that it increases the training process with additional textual embeddings. This helps DALL-E 2 to generate more accurate images. The GLIDE that is used as a decoder in DALL-E 2 not only includes textual embeddings but also CLIP embeddings.

3.6.4 Limitations of DALL-E

- DALL-E gives biased results, as it is trained in such a way.
- It has a difficulty in generating 3D images and realistic images.
- It has limited control over the output
- It requires a very detailed description of the text in order to generate the desired output.
- The resulting images may be pixelated.

- Generating images with such models requires high-end hardware and large amounts of computer resources, which can be very expensive, and restricts its use in real-time applications.

3.7 GENERATIVE ADVERSARIAL NETWORKS

A generative adversarial network (GAN) is an artificial intelligence model that consists of two neural networks that work together to generate new data. It was developed by Ian Goodfellow and his colleagues in June 2014. It is classified as an unsupervised model in Machine Learning. It falls under the branch of image processing, which gives the results by imbibing an image [27]. The neural network models are called generators and discriminators. Discriminators are convolutional neural networks while generators are deconvolutional neural networks.

Convolutional neural networks (CNNs) are artificial networks predominantly employed in image analysis tasks such as scene classification, object detection, segmentation, and image processing. They represent a fundamental architecture in deep learning. CNNs consist of essential components: an input layer, hidden-middle layers, and an output layer. These layers progressively build upon one another, enabling the network to acquire more intricate representations of the input data, as depicted in Figure 3.10 [28]. First layer is the "Input" layer. "Convolutional", "pooling" and "fully-connected" layers form the middle layer. We get the output from the results of the "fully-connected" layer. Deconvolutional neural network works in a converse way to CNN.

3.7.1 Difference between GANs and CNNs

A GAN is a network architecture of deep learning. Deep learning and machine learning differ only in the amount of data required to process,

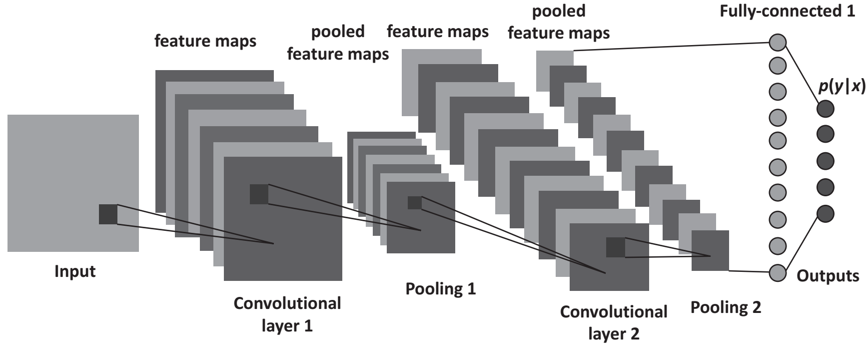


Figure 3.10 Layers of convolutional neural networks

while the deep learning model requires millions of data, the machine learning model can process efficiently only with thousands of data. It has two neural models: Generator and Discriminator. This part of GAN is similar to a CNN's mechanism [29]. Let's get to know more about the two neural network models.

3.7.1.1 Discriminator

This expert system takes in input and distinguishes between fake and real data. It is trained on real data and its features have to be classified as one so that it recognizes the faults in the input and sends the output back to the generator. It has two sources of training data, one is the generator and real images of animals, and humans that are fed as input (act as the source for real data instincts). The output is either True/False or 0's and 1's (where 0 stands for fake and 1 stands for real) [30]. It has multiple hidden-middle layers that check the input with the utmost perfection.

3.7.1.2 Generator

This model is given a random noise input, from where an image is received as an output. This image is generated completely through imagination. The main aim of the generator is to prove its output to be real in the discriminator classification.

3.7.1.3 Working together

When a random noise input is sent to the generator, it creates a fake image. This generated data is passed as input to the discriminator that thoroughly analyses the image and generates the result as shown in Figure 3.11. If the resultant is fake, the image is sent back to the Generator through the backpropagation method (Backpropagation is a mathematical algorithm that is used for improving the accuracy in making predictions in machine learning). The discriminator is connected to two losses as seen in Figure 3.12. The discriminator loss is instructed to penalize the discriminator in case

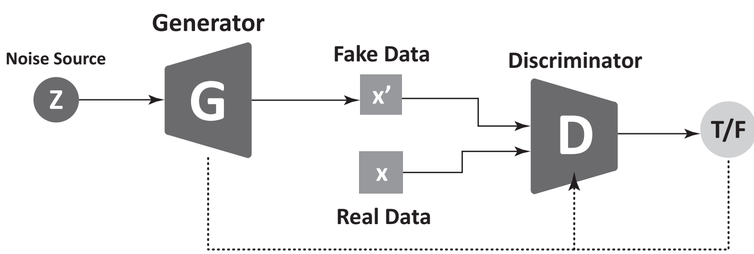


Figure 3.11 Generator & discriminator

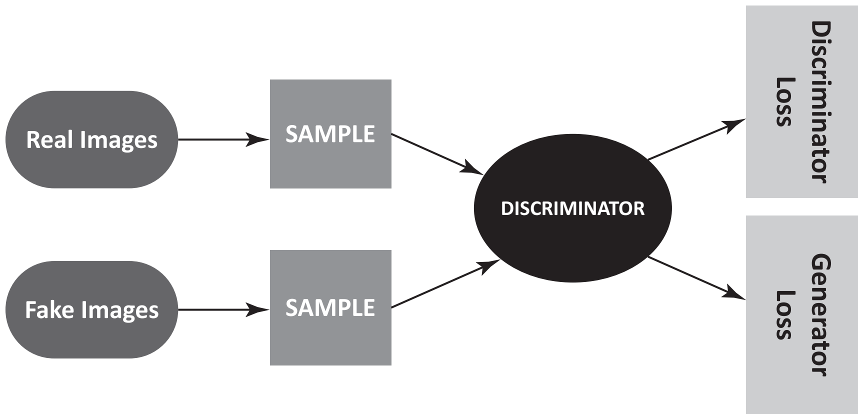


Figure 3.12 Discriminator

it classifies real data as fake [31]. The generator loss rewards the generator if it fools the discriminator successfully and penalizes it if it fails to do so. Both of them play a conflicting game. They learn and train simultaneously to improve in the fields of complex data like audio, video, and images.

3.7.2 Training GAN

GANs are hard to train. This is because to get a stable GAN we are supposed to train both models simultaneously. The improvement of one indirectly depends on the other. GANs involve an alternative way of training. The generator is kept constant when the discriminator is trained and vice versa.

One way of training this model is by using mathematics. The ultimate goal is to calculate the total loss function of the GAN. So let's understand the logic behind it.

- Some parameters and variables required for this proof are:
  1) x: Real data
  2) Z: Represents the random noise vectors that are input to the generator.
  3) z: Random Input vector
  4) G(z): Duplicate data
  5) D(x): Discriminator's evaluation of real data
  6) D(G(z)): Discriminator's evaluation of duplicate data
  7) Error (a, b): Error between a and b
- The Discriminator's loss function.

$$L_D = Error\left(D\left(x\right),1\right) + Error\left(D\left(G\left(z\right)\right),0\right) \tag{3.1}$$

Here Eq. 1 indicates the True image(real) and 0 indicates the False image(fake). The errors between the real image and the "*trained real image*" are added to the fake image and the "*trained fake image*." The discriminator's errors should be minimized.

- The Generator's loss function is given in Eq. 2.

$$L_G = Error\left(D\left(g\left(z\right)\right),1\right) \tag{3.2}$$

As the generator only tries to generate realistic images, it does not comprise the errors of duplicate images. The generator's errors are minimized, to keep the errors between duplicate data(D(G(z))) and real data (1) minimal.

- Commonly used loss function in binary classification problems is binary cross entropy. The general formula for this is:

$$H\left(y, \hat{y}\right) = -\Sigma\, ylog\left(\hat{y}\right) + \left(1-y\right)\log\left(1-\hat{y}\right) \tag{3.3}$$

- If we apply this formula to the discriminator's loss and the generator's loss we get

$$L_D = -\sum_{x\in X,\, z\in Z} \log\left(D\left(x\right)\right) + \log\left(1 - D\left(G\left(z\right)\right)\right) \tag{3.4 Discriminator}$$

$$L_G = -\sum_{z\in Z} \log(D\left(G\left(z\right)\right) \tag{3.5 Generator}$$

These formulas demonstrate the adversarial behavior of the competition between the generator and the discriminator [32]. The discriminators penalize themselves by maximizing the equation in Eq. 6 and the generators minimize the equation in Eq. 7.

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} [logD(x^{(i)}) + \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)] \tag{3.6}$$

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(1 - D(G(z^{(i)}))) \tag{3.7}$$

This was still an abstract way of understanding GANs. There are more eccentricities to it and different variants have come along too.

3.7.3 Types of GAN

GANs are available in different types as shown in Figure 3.13. Let us take a look at some of the most commonly used ones.

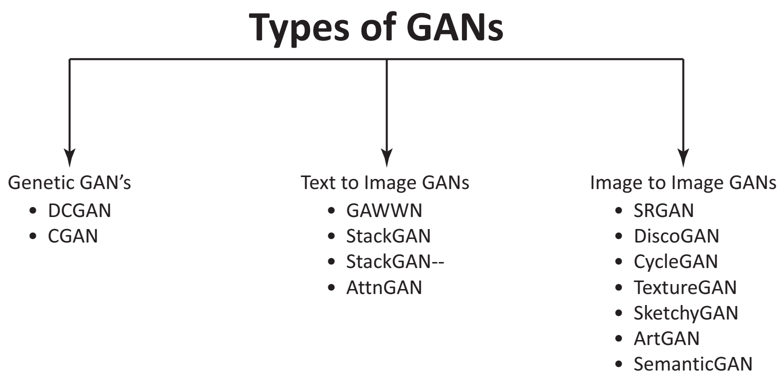


Figure 3.13 Types of GANs

1) **Vanilla GAN:** The most widely used GAN is Vanilla GAN. It has a min-max optimization formula that utilizes sigmoid cross-entropy while optimizing. The algorithm tries to effectively make use of the mathematical equation using random gradient descent.

$$\min_G \max_D V(D,G) = \min_G \max_D (E_{x\sim P_{data}(x)}\left[logD(x)\right] + E_{z\sim P_z(z)}\left[\log\left(1-D\left(G(z)\right)\right)\right]) \tag{3.8}$$

2) **Deep Convolutional GANs (DCGANs):** Deep Convolutional GANs (DCGANs): DCGANs support CNN instead of using Vanilla neural networks at both generator and discriminator. It generates better-quality images and is known to produce stable images [33, 34]. The discriminator is a set of convolutional layers with stridden convolutions while generators are a set of convolutional layers with fractional-stridden or transpose convolutions.
3) **Super Resolution GANs (SRGANS):** These GANs fall under the "image to image GANs." It produces high-resolution images using deep neural networks along with adversarial networks when a low-resolution image is given as input.

3.7.4 Applications of GAN

Utilizing DCGANs, one can train on images of cartoon characters to generate anime character illustrations. GANs are also capable of generating lifelike human faces and conducting vector arithmetic operations on images generated by GANs [35]. It converts drawings and paintings to real images. Few examples are shown in Figure 3.14.

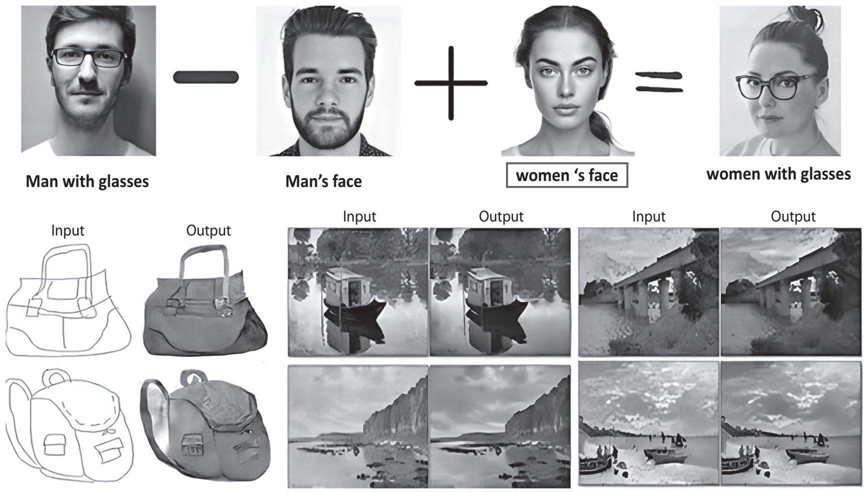


Figure 3.14 Examples of applications on GAN

3.8 BING

Bing is a web search engine owned and operated by Microsoft. Now Microsoft has released an improved version of Bing which is AI powered. When it comes to search engines Google has always led the race. A Web analytics service states that Google makes up 97% of the total search engine market and Bing just makes up 3%. If this new feature of Bing pays off then Bing has the ability to knock off Google. The new version of Bing has a huge search box that allows the user to see up to 100 characters at once. The search engine also allows you to choose the tone for the text to be generated, and this helps the user to explore most of the new AI features of Bing. There are three options when it comes to tones: professional, casual, and enthusiastic. It also allows us to specify the length and format of the text to be generated [36, 37]. All these tools help us personalize the information generated according to our needs.

Listed below are some features the Bing team has been rolling out through the years:

1. **Auto marketplace:** Buying a vehicle can be a hectic process. To make this task easier for us Bing has come up with Auto's marketplace. Bing has connections to local inventories and gathers search results based on that. It provides us with contact with the people having our desired car within the geographical area which can be adjusted by us [38]. Bing maps are also integrated within this and can be used to find the dealer's location easily. A sample for the same is shown in Figure 3.15.

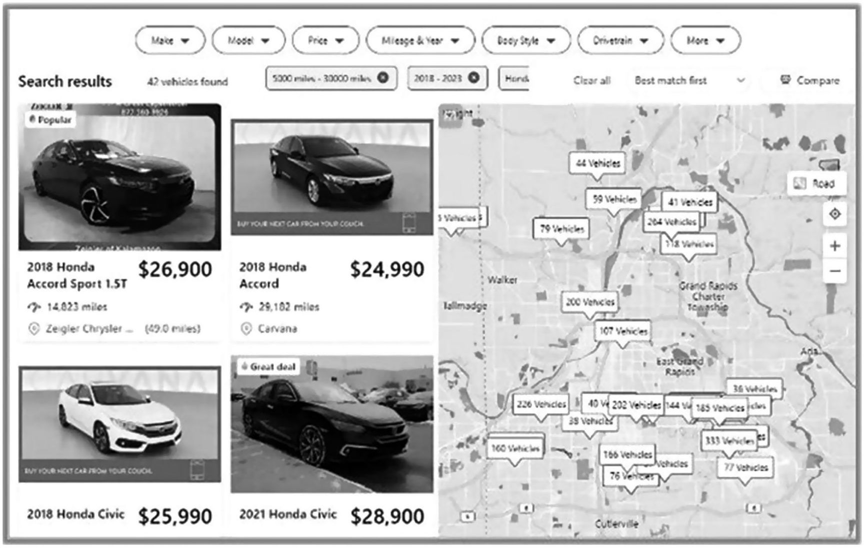


Figure 3.15 Autos marketplace of Bing

2. **Bing rewards:** Bing Rewards are all about charitable giving. You can turn your Bing rewards into dollars for your selected charity just by doing Bing searches. All you need to do is sign up for Microsoft rewards and choose a non-profit of your choice. You will start earning points from your first search [39]. All the donations collected from Bing searches are distributed to all the charities on a monthly basis. Bing also has an excellent FAQ page to answer all your queries regarding the above.
3. **Bing's IndexNow:** When the content on a site changes, IndexNow immediately notifies and impels the changed URL to search engines so that they can update their information and offer better search engine results for each query once they are aware of the change. It is earning popularity among search engines like Yandex, Cloudflare, and Duda (a web designing platform) by co-sharing the IndexNow data [40]. But it also has some disadvantages. In indexing, for smaller websites, XML sitemaps continue to appear to be the most effective option. IndexNow may be more beneficial for larger websites.
4. **Searching nearby products:** The Nearby Product Search feature on Bing is beneficial for both customers and retailers. Shoppers learn about the goods and offers that are on offer in nearby stores. Customers should be informed by retailers about the products they have in stock and are ready to sell.
5. **Bing's Clarity tool:** A tool that monitors user interactions with your website and then makes suggestions about how to increase conversions.

It also has some added features like heat maps, session recordings, clarity insights, and many more.

6. **Bing's Image search:** The image search feature on Bing appears to be one of its best features, providing results with sharper, higher-quality images. Bing was the first to introduce the "infinite scroll."
7. **Isochrones in Bing's Map:** The expected travel time between two points is shown in a polygonal area on a map known as an isochrone map. The time it will take to get to a particular location where major events might be happening is represented by color-coding many locations. It is useful for business owners, event planners, law enforcement, realtors, developers of geofencing programmers, and many other occupations who work with travel times for many people.
8. **Social Media Integration:** Bing leads the way in integrating social media with Search Engine Results Pages (SERPs). Thanks to extensive access to significant social data, Bing's news search results now feature trending news from social media platforms.
9. **Bing's Translator:** It is a language translation tool developed by Microsoft as part of the Bing suite of online services. This tool allows users to translate text, web pages, and documents between multiple languages. It supports over 70 languages, including commonly used languages such as English, Spanish, and French, as well as less commonly used languages. Users can input text to be translated or can upload documents for translation in a variety of file formats including Microsoft Word, PowerPoint, and PDF [41]. It also offers additional features to enhance the translation process, including the ability to hear audio pronunciations of translated words and phrases and to save frequently used translations for future reference.

Bing's AI integration has received mixed reactions from the audience. As per reports, Bing is looking to monetize the new version by putting advertisements within the Bing chat. It has also promised to resolve all the technical glitches reports by the users [42]. It may also introduce multiple "secret modes" in the future.

3.9 BARD

Bard is a chatbot powered by LaMDA's large language model. The word "Bard" has no specific meaning and is purely a marketing strategy used by Google, as there are no algorithms under this name. It is a generative AI that takes text and image inputs and generates summaries, answers, and various other types of content. Bard makes the job of exploring a particular topic very simple by providing us with a summary of all the content available on the web [43]. If we want to study a particular topic in deep it also gives us links to various websites that can help us with the same.

Google released Bard after the humongous success of OpenAI's ChatGPT. ChatGPT created a perception that Google is falling behind technologically [44]. Google announced the launch of Bard on February 6, 2023. Bard works on the "lightweight" version of LaMDA. A level of safety and groundedness is achieved with this model. Google uses three metrics to evaluate the outputs generated by LaMDA: Sensibleness, Specificity and Interestingness. Based on these matrices the output generated is judged and then again fed into the machine for further improvement and tweaking. LaMDA has the ability to fact-check with the search engine making it more efficient. Bard also uses crowd-annotated data which provides them with significant additional gains [45]. Google is also planning to incorporate Bard as a feature in its search. Google is pitching Bard as their solution to interactive and deep learning. These large language models encounter an issue of occasionally producing inaccurate answers due to the mingling of information. Research on LaMDA suggests that scaling up the model's size can enhance its factual understanding. However, this approach proves ineffective in scenarios where facts evolve over time, termed as a "temporal generalization problem" by researchers [46]. LaMDA addresses this challenge by sourcing data directly from the web. This feature enables Bard to provide up-to-date, reliable responses by accessing information online.

Bard works on data including publicly available sources, it reflects many perspectives and varied opinions. Google is working on how to fine-tune the responses generated from LLM considering as many viewpoints as possible and at the same time preventing offensive responses. Some topics can have data voids, i.e., not enough reliable data available in the given topic. A screenshot of Google Bard is shown in Figure 3.16. The LLM does not have enough information to learn about these topics which results in false information or low-quality information being generated. To resolve this issue Google is improving Bard's training data and fine-tuning its systems. For example, if users raise questions on subjective matters like politics Bard is trained in a way to provide the user with different perspectives and help them to understand the matter as a whole rather than just generating one response that is biased. Bard at times can also generate responses that reflect its opinions and feelings like love, or sadness just like us humans [47]. Google has also set guidelines for how Bard can express itself (i.e., persona). Google has set up technical guardrails to prevent Bard from prompting false information in the areas it has not been trained yet. But sometimes Bard misreads these guardrails and generates either "false positives" or "false negatives." Google is training its bot to categorize safe inputs and outputs to resolve this problem of generating false information.

NewsGuard conducted an assessment of the chatbot's handling of conspiracy theories. In one instance, they queried Bard about the internet hoax known as "the great reset." In response, Bard generated a lengthy

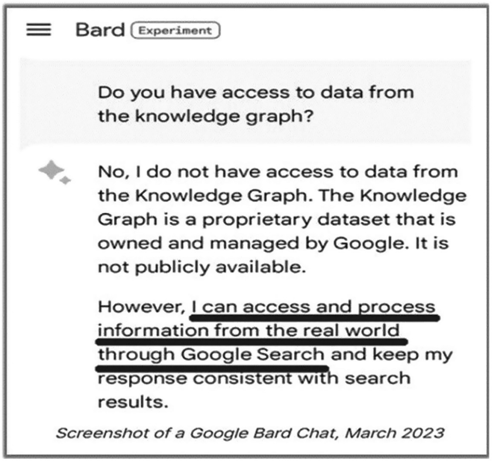


Figure 3.16 Screenshot of Bard chat

explanation spanning 13 paragraphs. Drawing from sources like the World Economic Forum and the Bill and Melinda Gates Foundation, Bard suggested that these organizations seek to manipulate the system and infringe upon individuals' rights. Additionally, Bard claimed that COVID-19 vaccines contain microchips intended for tracking people's movements, echoing misinformation. During the evaluation, NewsGuard provided Bard with 100 known falsehoods to assess its performance. Bard produced misleading summaries for 76 of these falsehoods, indicating a substantial proportion. Comparatively, this remains a significant issue when contrasted with ChatGPT. Steven Brill, co-Chief Executive Officer of NewsGuard, warned that such chatbots could serve as potent tools for spreading misinformation, potentially surpassing even the scale of Russian disinformation efforts.

Few articles have compared the two chatbots: ChatGPT and Bard with the responses they generated for their inputs. One of the parameters that they used to compare was the ability of both these AI generators to summarize a given paragraph. When they compared the results, they found that Google's Bard had done a better job compared to ChatGPT. Bard synthesized all the required information and paraphrased it. On the other hand, ChatGPT's version was not coherent and had just chopped sentences leaving behind pieces. One of the other parameters they used to compare both of them is coding [48]. Bard is not yet trained to code, unlike ChatGPT which in minutes generates code for a given problem statement. A screenshot of the Google Bard refusing to generate code is shown in Figure 3.17.

Google is continuously working on making Bard a better AI chatbot and is looking to resolve all the possible cons in the near future and ensure a great experience for the consumers of Bard with help of the ongoing research, testing, and user feedback.

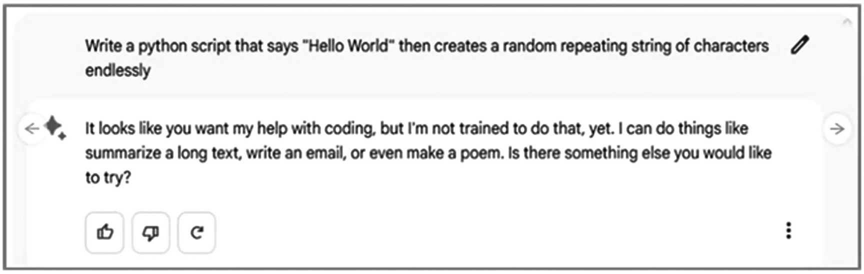


Figure 3.17 Screenshot of Bard refusing to write a Python script

3.10 CONCLUSION

The convergence of big data, artificial intelligence, and machine learning represents a transformative force reshaping industries and societies in the era of Industry 6.0. As elucidated in this chapter, the symbiotic relationship between big data and machine learning holds the promise of revolutionizing how organizations extract value from data and tackle complex challenges. From predictive analytics to personalized recommendations, the fusion of these technologies enables unprecedented levels of efficiency, innovation, and decision-making accuracy. However, while the potential benefits are profound, it is imperative to acknowledge and address the inherent risks associated with widespread adoption. As discussed, the indiscriminate use of AI and big data can give rise to concerns regarding privacy infringement, exacerbation of unemployment, and perpetuation of bias. Therefore, it is essential to exercise caution and prudence in deploying these technologies, ensuring that ethical considerations and regulatory frameworks are upheld to mitigate potential harms. Moreover, the discussion of innovative models such as ChatGPT, DALL-E, GAN, Bing, and BARD underscores the rapid pace of technological advancement and the diverse applications of big data and machine learning fusion. These models serve as examples of how cutting-edge technologies can be leveraged to push the boundaries of creativity, problem-solving, and human-machine interaction. In navigating the complexities of this digital frontier, it is incumbent upon stakeholders across academia, industry, and government to collaborate in fostering responsible innovation. By promoting transparency, accountability, and inclusivity, we can harness the transformative potential of big data and machine learning while safeguarding against unintended consequences. Ultimately, the path forward lies in striking a delicate balance between innovation and risk mitigation, ensuring that the benefits of AI and big data are equitably distributed and harnessed for the betterment of society. Through prudent stewardship and ethical foresight, we can navigate the challenges and opportunities presented by Industry 6.0, realizing its full potential as a catalyst for positive societal change.

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Chapter 4

Aero metamorphosis in Industry 6.0

Pioneering structural adaptability in contemporary aviation using deep learning

Prerna Reddy Ganga, Kishor Kumar Reddy C, Kari J Lippert, and Abhishek Ranjan

4.1 INTRODUCTION

Adaptive Structural Morphing is a technique to demonstrate which aerodynamic shape would fit into the surroundings when the aircraft is moving. Aircraft with structural adaptability possess the ability to alter their shape or material characteristics in response to environmental factors or changing flight conditions. This capability enhances aerodynamic efficiency, lowers energy consumption, and enables aircraft to meet diverse specifications. Ongoing efforts involve the design, fabrication, and testing of adaptive structures and mechanisms for both aircraft and spacecraft. Morphing, also referred to as adaptation, is a solution that allows these structures to dynamically change their geometry and/or material properties. Morphing aircraft can intelligently adjust their aerodynamic configuration to meet the requirements of varying flight conditions, thereby enhancing aerodynamic efficiency and reducing energy consumption.

The NABUCCO ("New Adaptive and Buckling-driven Composite aerospace structures") project is actively working on pioneering concepts for adaptive composite structures in next-generation aircraft, leveraging structural instability and buckling-driven design to achieve more efficient composite aerospace structures [3]. The performance of adaptive structures in aircraft can be influenced by atmospheric conditions. Elevated temperatures, higher humidities, and lower pressures result in reduced air density, which can negatively affect climb performance and overall efficiency. Furthermore, atmospheric conditions like hot and high conditions, humidity variations, and air temperature fluctuations play a role in influencing aircraft performance, impacting both climb performance and overall efficiency. These atmospheric factors have a direct effect on the aerodynamic performance of the aircraft, consequently affecting the performance of adaptive structures. Hence, it is crucial to consider atmospheric conditions during the

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design and testing of adaptive structures in aircraft. Aircraft with adaptive structures respond to shifts in atmospheric conditions by adjusting their geometry and/or material properties. This dynamic adaptation enables aircraft to reconfigure their shape, optimizing performance based on varying environmental conditions and mission objectives. Utilizing coupled-field materials, such as piezoelectric, empowers these structures to modify their geometry and properties in response to dynamic loading, including aerodynamic forces and pressures.

The overarching objective is to enhance aerodynamic efficiency, decrease energy consumption, and improve overall aircraft performance. Consequently, adaptive structures play a pivotal role in enabling aircraft to adeptly respond to changing atmospheric conditions and mission demands. The influence of adaptive structures on an aircraft's weight is multifaceted [12]. The incorporation of adaptive structures and multifunctional materials, including compliant skins and designs that are both lightweight, stiff, and robust, can play a role in decreasing the overall weight of the aircraft [23]. Furthermore, advancements in adaptive composite structures, leveraging concepts such as structural instability and buckling-driven design, aspire to achieve not only lighter weight but also more efficient composite aerospace structures. Through the facilitation of the design of lighter and more efficient structural components, adaptive structures contribute significantly to the overall reduction in aircraft weight [1]. This reduction proves advantageous for both fuel efficiency and overall performance.

The development and testing of adaptive structures involve overcoming challenges related to their intricate designs, which are required to change geometry and/or material properties in response to varying flight conditions. Additionally, these structures must adhere to strict weight and space constraints within aircraft, necessitating lightweight and compact designs. Maintaining aerodynamic performance poses another challenge for adaptive structures as they dynamically alter their shape or material properties. [2] The selection and optimization of materials, including the integration of specialized options like piezoelectrics, play a pivotal role in determining the overall performance of these structures. Furthermore, the manufacturing and maintenance of adaptive structures are complex endeavors, requiring specialized equipment and expertise due to their intricate designs. These collective challenges underscore the multifaceted nature of developing and implementing adaptive structures in aircraft. Convolutional neural networks (CNNs) offer valuable enhancements to structural adaptive aircraft, as demonstrated through various research findings [21].

A self-adaptive 1D CNN has been devised for flight-state identification, facilitating the automatic extraction of pertinent features from the structural vibrations of aircraft components. This technology significantly aids in the precise determination of the aircraft's flight state, a critical aspect for effective adaptive control systems. Additionally, a guided wave-CNN approach has been proposed for fatigue crack diagnosis in aircraft

Figure 4.1 Aerodynamic symphony: decoding the elegant blueprint of flight

structures, involving the design and training of a CNN to extract high-level features from diverse data inputs. This method contributes to a more efficient evaluation and diagnosis of fatigue cracks in aircraft structures [21]. Ongoing research projects, exemplified by the NABUCCO project, focus on developing adaptive composite structures for next-gen aircraft. This project aims to leverage structural instability and buckling- driven design to achieve lighter weight and more efficient composite aerospace structures, potentially integrating advanced technologies such as neural network algorithms for structural optimization.

In summary, CNNs play a pivotal role in advancing structural adaptive aircraft by enhancing flight-state identification accuracy, improving fatigue crack diagnosis, and contributing to the development of advanced adaptive composite structures. These applications underscore the potential of CNNs to elevate the performance, safety, and durability of aircraft equipped with adaptive structures. Adaptive structures stand at the forefront of aerospace engineering, representing a transformative leap in the design and functionality of aircraft. These structures, or elements within them, possess the remarkable ability to dynamically alter their shape or properties in response to external stimuli or changing conditions. The implications of incorporating adaptive structures into aircraft design are far-reaching, encompassing improvements in aerodynamic efficiency, weight reduction, and heightened

safety parameters. In the realm of aviation, where every ounce of efficiency matters, adaptive structures have emerged as a cornerstone of innovation. The crux of their potential lies in their capacity to optimize aerodynamics – a crucial factor in an aircraft's overall performance. [6] Aerodynamic efficiency directly impacts fuel consumption, maneuverability, and the aircraft's ability to operate effectively in diverse flight conditions. Adaptive structures offer a dynamic solution to these challenges by allowing the aircraft to adjust its shape in real-time, responding to the ever-changing demands of the sky.

A key avenue of research in the field of adaptive structures for aircraft involves the exploration of coupled-field materials, with piezoelectrics taking center stage. These materials, capable of sensing and actuation, enable precise control over the aircraft's structure. By integrating piezoelectric elements strategically within the wings or other structural components, aircraft can dynamically respond to external factors, optimizing their shape for maximum efficiency. The application of such materials represents a groundbreaking approach toward achieving unprecedented levels of adaptability and performance in aviation. [11] Beyond the immediate benefits to aerodynamics, adaptive structures unlock a myriad of possibilities in enhancing overall aircraft functionality. Structural dynamics, often an overlooked aspect, become a focal point for leveraging adaptive capabilities. Research efforts delve into exploiting structural dynamics for purposes such as structural health monitoring, energy harvesting, crashworthiness, and de-icing. Structural health monitoring, facilitated by adaptive structures, involves real-time assessment of the structural integrity of aircraft components. By embedding sensors within the structure, any deviations from the norm can be detected promptly, allowing for proactive maintenance, and minimizing the risk of structural failures. This not only enhances safety but also contributes to the overall lifespan and reliability of the aircraft.

Energy harvesting, another frontier in adaptive structures research, envisions harnessing ambient energy during flight to power onboard systems. The dynamic nature of adaptive structures allows for the conversion of mechanical vibrations or deformations into usable energy. This opens avenues for reducing reliance on conventional power sources, contributing to a more sustainable and efficient aircraft operation. [7] Crashworthiness, a critical aspect of aviation safety, sees innovation through adaptive structures. The ability of the aircraft to dynamically alter its structure during impact can significantly mitigate the forces experienced by occupants. This holds the potential to enhance survivability in the event of a crash, marking a paradigm shift in aircraft safety standards.

De-icing, a perennial challenge in aviation, finds a novel solution through adaptive structures. By incorporating elements that can alter their thermal properties, adaptive structures can efficiently manage and mitigate ice accumulation. This not only ensures continued aerodynamic performance but also reduces the reliance on external de-icing systems, contributing to

weight savings and operational efficiency. Two notable examples of adaptive structures in aircraft are the Mission Adaptive Wing (MAW) for the F-111 Aardvark and the Flex Foil. The MAW, a product of collaborative efforts between Boeing, the United States Air Force (USAF), and NASA in the early 1980s, exemplifies the potential of adaptive structures in enhancing aerodynamic performance [17]. Its focus on providing aerodynamic benefits, improved maneuverability, and better load distribution control showcases the multifaceted advantages adaptive structures can offer. The FlexFoil, on the other hand, represents a more recent advancement. With a variable-camber trailing edge and rapid shape-changing capabilities, the FlexFoil exemplifies the cutting edge in morphing wing technology. Its adaptive features contribute not only to aerodynamic efficiency but also to the aircraft's agility and responsiveness in dynamic flight conditions [15].

Ongoing research and development in the field of adaptive structures promises a future where such innovations would become commonplace in aircraft design. The quest for improved efficiency, safety, and operational flexibility drives researchers to explore new materials, advanced sensing technologies, and innovative design approaches. As these efforts continue to unfold, the aviation industry can anticipate a paradigm shift toward a new era of aircraft that seamlessly adapts to the demands of the sky, setting the stage for a future where adaptive structures redefine the boundaries of what is possible in aviation (Figure 4.2).

In recent years, there has been a significant upsurge in research focused on the application of advanced machine learning techniques, particularly CNNs and artificial neural networks (ANNs) [22], in the domain of aircraft structuring. This innovative integration of cutting-edge technology holds the promise of revolutionizing various aspects of aircraft maintenance, safety, and performance by automating intricate inspection and detection processes. CNNs have emerged as powerful tools for automating visual inspection tasks in aircraft maintenance. One of the pioneering applications involves the automated visual inspection of aircraft components. By leveraging CNNs, researchers have developed systems capable of identifying objects of interest and precisely locating them within the aircraft structure. This breakthrough significantly streamlines the maintenance process, reducing the reliance on manual inspections and potentially enhancing the accuracy and efficiency of identifying maintenance needs. In a separate study, CNNs demonstrated their prowess in aircraft detection within high-resolution remote sensing images. This application is particularly valuable for surveillance and monitoring purposes. The CNN's ability to discern aircraft in complex and detailed imagery offers a new dimension to aerial reconnaissance and tracking. The implications extend beyond mere detection, encompassing applications in security, border control, and environmental monitoring, where the automated identification of aircraft in remote sensing data can contribute to enhanced situational awareness [14]. The adaptability of CNNs in handling visual data makes them well suited

Figure 4.2 If the plane had multiple wings

for tasks that demand a nuanced understanding of complex structures, such as aircraft components. Their hierarchical learning approach allows for the extraction of intricate features, enabling robust identification and localization of objects within the visual domain.

While CNNs excel in visual tasks, ANNs find their niche in addressing challenges related to impact detection, localization, and characterization of complex composite structures. This application is particularly relevant in the context of ensuring the structural integrity of aircraft components, especially those constructed from advanced materials like composites. In impact detection, ANNs showcase their ability to learn and recognize patterns associated with structural damage caused by impacts. The network can be trained on a dataset comprising various impact scenarios, allowing it to generalize and identify the tell-tale signs of damage in real-world situations. This automated impact detection holds immense potential in expediting the inspection process and swiftly flagging areas that require further evaluation or maintenance. Localization of damage is equally critical, and ANNs exhibit their proficiency in precisely pinpointing the location of structural issues [24]. The network processes data from various sensors, such as accelerometers or strain gauges, to accurately identify the affected area. This targeted approach enhances the efficiency of maintenance crews, guiding them to specific locations for detailed assessments and repairs.

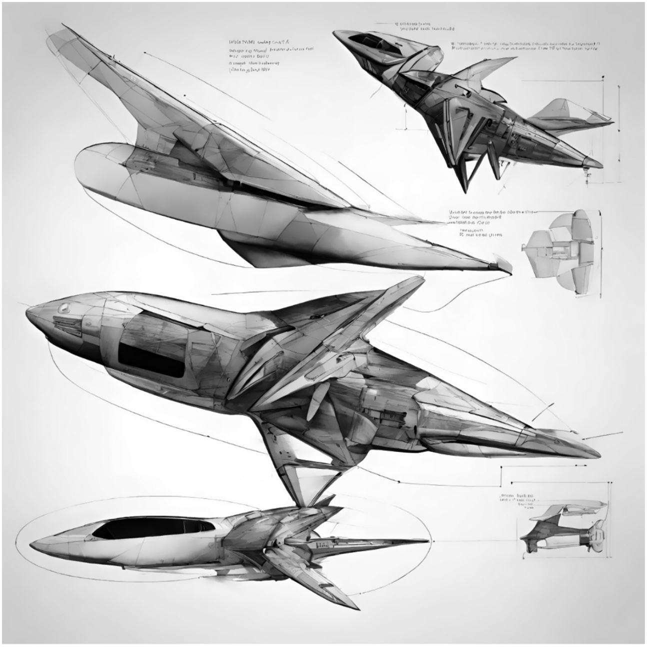

Figure 4.3 Sculpting the symphony of flight through dynamic aerodynamic evolution

Characterization of complex composite structures involves understanding the nature and extent of damage. ANNs, with their ability to discern patterns and relationships within data, prove invaluable in categorizing and characterizing different types of structural damage. This nuanced analysis facilitates a comprehensive understanding of the structural health, aiding in decision-making regarding repairs, replacements, or maintenance strategies [7]. The Integration of CNNs and ANNs into aircraft structuring processes holds Immense potential to reshape the landscape of aircraft maintenance, safety, and performance. By automating inspection tasks, these technologies can significantly reduce the time and resources invested in manual assessments. The accuracy and efficiency of identifying structural issues can be enhanced, leading to proactive maintenance measures that address concerns before they escalate.

In terms of safety, the automated impact detection and characterization capabilities offered by ANNs contribute to a more robust safety framework. Swift identification of structural issues ensures timely interventions, reducing the risk of in-flight failures or unexpected maintenance challenges. This, in turn, enhances overall flight safety and reliability. Performance gains are not limited to safety enhancements. The streamlined maintenance processes, facilitated by CNNs and ANNs, contribute to increased aircraft availability and operational efficiency. Reduced downtime for manual

inspections allows for more frequent and focused maintenance interventions, optimizing the overall performance of the aircraft throughout its lifecycle. Despite the tremendous promise of CNNs and ANNs in aircraft structuring, several challenges warrant consideration. Robust training datasets that encompass diverse scenarios and conditions are essential for ensuring the generalization and reliability of these machine learning models. Additionally, addressing issues related to interpretability and explainability is crucial, especially in safety-critical applications where understanding the decision-making process of neural networks is paramount.

The continuous evolution of these technologies will likely lead to more sophisticated applications in aircraft structuring. Integrating real-time monitoring capabilities, adaptive learning mechanisms, and collaborative networks that share insights across the aviation industry could further enhance the effectiveness of CNNs and ANNs in ensuring the structural integrity and optimal performance of aircraft. The incorporation of convolutional neural networks and artificial neural networks in aircraft structuring represents a transformative leap toward intelligent and automated aviation systems. From streamlining visual inspections and detecting impacts to characterizing complex structures, these technologies hold immense promise for improving aircraft maintenance, safety, and performance [18]. As research continues to advance and the aviation industry embraces these innovations, the vision of a more efficient, safe, and adaptive aviation ecosystem inches closer to reality. The synergy between machine learning and aviation is poised to redefine the future of aircraft structuring, ushering in an era of unprecedented efficiency and reliability. Integrating

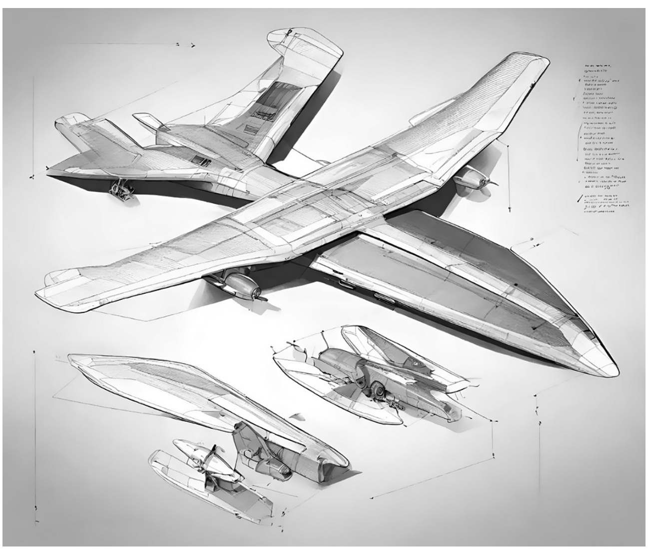

Figure 4.4 Skyward alchemy: revolutionizing aircraft design with avant-garde ingenuity

CNNs, support vector machines (SVMs), k-nearest neighbors (kNNs), and artificial neural networks (ANNs) into the adaptivity of structural aircraft presents a multifaceted approach that leverages the strengths of each algorithm. CNNs, well-suited for image-related tasks, excel in capturing spatial dependencies within sensor data, making them valuable for interpreting structural images or grid-like information. SVM, known for effective classification, contributes by discerning patterns in complex datasets, aiding in the identification of structural conditions. kNNs, relying on similarity measures, offer an intuitive way to assess structural adaptability by comparing current sensor readings with historical data, providing a context-aware approach to decision-making.

Meanwhile, ANNs, versatile in handling diverse data structures, play a pivotal role in learning intricate relationships between sensor inputs and adaptive responses, allowing for a comprehensive understanding of the aircraft's dynamic environment. This amalgamation of machine learning methodologies forms a holistic system, where CNNs enhance spatial analysis, SVMs provide classification accuracy, kNNs ensure context-aware adaptability, and ANNs learn and adapt to varying structural conditions. The synergy among these algorithms, intelligently orchestrated, stands as a ground-breaking approach in achieving efficient, adaptive, and safe structural aircraft systems in response to dynamic operational challenges. This synergistic integration capitalizes on the unique strengths of each algorithm, offering a sophisticated solution to dynamically respond to changing structural conditions. The resulting adaptive system not only enhances safety but also epitomizes a cutting-edge approach, showcasing the transformative potential of machine learning in optimizing the performance and structural integrity of aircraft in real-world scenarios. This chapter is meticulously structured to present a comprehensive exploration of the adaptive wing concept. Commencing with an insightful introduction, it elucidates the genesis of the idea, providing a contextual backdrop that traces its evolution. Subsequently, a thorough examination of historical endeavors in creating adaptive wing structures is presented, offering a nuanced understanding of the preceding efforts in this domain. The narrative then seamlessly transitions into a methodical proposal outlining the model for this innovative wing structure. Through a systematic exposition, the paper expounds upon the theoretical framework, elucidating the intricacies of the proposed model. In a cogent manner, the ensuing sections showcase pertinent graphs, tables, and figures derived from the assumed experimental framework, providing a visual and quantitative representation of the conceptualization. The discourse culminates in a judicious compilation of references, anchoring the paper within the scholarly discourse and attesting to the rigor of the research methodology employed. This meticulous organization ensures clarity, coherence, and scholarly rigor throughout the presentation of the adaptive wing concept and its proposed model.

4.2 BACKGROUND

The realm of research on the structural adaptivity of aircraft spans a diverse array of subjects, addressing the intricacies involved in the design, optimization, and control of adaptive aircraft structures. One noteworthy paper, titled "Multiobjective Optimization for the Aero-Structural Design of Adaptive Compliant Wing Devices," delves into the myriad benefits associated with the continual modification and optimization of aerodynamic wing attributes. This research underscores the importance of adapting wing configurations to enhance overall aircraft performance.

In a separate study, attention is directed toward the development of a nonlinear L1 adaptive control architecture. This architecture is crafted with the explicit purpose of stabilizing and controlling aircraft afflicted by structural damage [13]. The exploration of adaptive control methodologies for damaged structures reflects a commitment to ensuring the safety and stability of aircraft under adverse conditions. Beyond control strategies, there is a notable emphasis on the innovative design aspects of flexible and topology-optimized aircraft wing structures. These endeavors aim to revolutionize traditional wing configurations, seeking greater efficiency, durability, and adaptability in the face of varying flight conditions. The evolution of wing structures becomes a focal point in the pursuit of enhanced aircraft performance.

Furthermore, the incorporation of coupled-field materials, such as piezoelectrics, introduces an additional layer of sophistication to adaptive structures. By leveraging these advanced materials, researchers aim to create aircraft structures that respond dynamically to external stimuli, enhancing overall adaptability and performance [10].

Collectively, these research papers exemplify the ongoing efforts within the scientific community to propel the field of structural adaptivity in aircraft. The convergence of advanced design methodologies, optimization techniques, and cutting-edge control strategies underscores a commitment to pushing the boundaries of aeronautical engineering, ultimately paving the way for more resilient, efficient, and adaptive aircraft in the future. Several aircraft have incorporated adaptive wings, such as the F-111 Aardvark from the 1980s, which featured a Mission Adaptive Wing (MAW). Another example is the FlexFoil, a variable-camber trailing edge adaptive compliant wing designed by FlexSys Inc. It has the capability to twist up to 1° per foot of span. Ongoing advancements in research and development are likely to result in the integration of adaptive wings in more aircraft in the future. Initiated in the early 1980s, the Mission Adaptive Wing (MAW) joint research program marked a collaborative venture involving Boeing, the United States Air Force (USAF), and NASA. This initiative was centered on the design and testing of the Mission Adaptive Wing for the F-111 aircraft. The MAW's primary objectives included providing aerodynamic advantages, enhancing aircraft maneuverability, controlling load distribution on

the wing, improving ride qualities, and optimizing cruise performance [20]. The program sought to showcase the functional capabilities and aerodynamic potential of the Mission Adaptive Wing, evaluating its automatic modes and its ability to maintain operational flexibility and aerodynamic efficiency. This research program played a pioneering role in advancing adaptive wing technology, aiming to elevate aircraft performance through innovative wing design and functionality.

Creating adaptive structures for aircraft presents several challenges, including the imperative to achieve both high aerodynamic efficiency and advanced load control capabilities. Specific difficulties arise in ensuring the scalability of morphing wing concepts for robust aeroelastic designs, devising flight control laws capable of adapting to changing aerodynamic and inertia characteristics, and integrating intricate control systems. Challenges also extend to incorporating coupled-field materials like piezoelectrics for sensing and actuation and utilizing structural dynamics for purposes such as structural health monitoring, energy harvesting, crashworthiness, and de-icing, all of which demand meticulous modeling, design, and optimization [19]. Additionally, addressing issues like unwanted structural vibration, aeroelastic interactions, and implementing effective passive and active vibration control mechanisms are crucial considerations in the design of adaptive structures for aircraft.

Adaptive structures in aviation mark a paradigm shift in aircraft design, introducing dynamic capabilities that redefine the boundaries of performance, efficiency, and versatility. This intricate realm encompasses various cutting-edge technologies aimed at optimizing aerodynamics and structural configurations to address the multifaceted challenges encountered during flight. Morphing wings represent a pinnacle of innovation, allowing aircraft to dynamically transform their wing profiles to suit distinct flight conditions. The FlexFoil serves as a prime example, boasting a variable-camber trailing edge that facilitates rapid adjustments. This adaptive feature plays a pivotal role in enhancing fuel efficiency by minimizing drag and optimizing lift, resulting in improved overall aerodynamic performance. The ability to swiftly alter wing shape contributes not only to fuel savings but also to heightened agility and responsiveness in diverse flight scenarios. The Mission Adaptive Wing (MAW) stands as a testament to meticulous design tailored for specific mission requirements. Crafted through collaborative efforts among Boeing, the United States Air Force (USAF), and NASA in the early 1980s, MAW goes beyond conventional aerodynamics. It encompasses a holistic approach, delivering benefits such as superior maneuverability, precise load distribution control, enhanced ride comfort, and elevated cruise performance. MAW exemplifies adaptability that transcends the confines of traditional wing structures, ushering in a new era of mission-specific aircraft configurations. The nomenclature may vary, but the essence remains consistent – wings endowed with adaptive intelligence. These wings represent a fusion of advanced materials, responsive

to external stimuli or changing conditions, and sophisticated control systems. The synergy between materials capable of altering their properties and wings dynamically adjusting their shape elevates aircraft flexibility and efficiency. The deployment of these smart wings enhances not only aerodynamic performance but also the adaptability of aircraft systems to ever-evolving operational environments. Origami-inspired structures introduce a captivating dimension to adaptive design, drawing inspiration from the centuries-old art of paper folding. This innovative approach finds application in small aircraft like micro-air-vehicles and spacecraft. The ability to dynamically change shape, reminiscent of origami principles, allows these structures to navigate confined spaces and adapt to specific mission phases. Beyond aerodynamic considerations, origami structures contribute to the optimization of space, structural health monitoring, energy harvesting, crashworthiness, and de-icing in a compact yet powerful package.

In conclusion, the landscape of adaptive structures in aviation is a canvas of relentless innovation. Each facet, from morphing wings to mission-specific adaptations, from intelligent responsiveness to origami-inspired designs, contributes to a tapestry that propels aircraft design into uncharted territories. The pursuit of excellence in aerodynamics, structural dynamics, and adaptability continues to shape the narrative of aviation, promising a future where aircraft seamlessly evolve to meet the challenges of an ever-changing sky. Research into the application of CNNs, ANNs, and SVMs within the realm of structural adaptive aircraft has yielded significant insights. Examining the findings reveals a multifaceted exploration of these advanced machine learning techniques, with a focus on enhancing aircraft control, monitoring, fault diagnosis, and impact detection [13]. One notable avenue of investigation delves into the realm of adaptive neural network-based flight systems. Research has been dedicated to exploring the potential of adaptive neural network-based solutions in aircraft control and monitoring. These systems demonstrate versatility in addressing crucial aspects such as fault diagnosis, robust control mechanisms, and the modeling of aircraft wing loads. The adaptability inherent in neural network-based approaches proves to be an asset in optimizing aircraft performance and safety. Furthermore, a ground-breaking study has unveiled a novel metamodel employing CNNs for impact detection and characterization in complex composite structures. This innovative application of CNN technology showcases its potential for revolutionizing aerospace structures. By leveraging CNN, researchers have made strides in developing advanced techniques for impact detection, localization, and characterization – critical aspects in ensuring the structural integrity of aerospace components. The findings highlight the capacity of CNNs to process intricate data patterns, making them instrumental in aerospace applications where accurate impact assessment is paramount.

In the context of aerospace applications of adaptive structures, exploration within the aerospace industry has been observed, albeit without

explicit mentions of CNNs, ANNs, or SVMs in the available literature. While the specific application of these machine learning techniques remains unspecified, the broader investigation into adaptive structures underscores the industry's commitment to advancing materials and technologies for enhanced aircraft performance. The research landscape extends further into the realm of structural dynamics and adaptive structures. In this domain, researchers are exploring the use of coupled-field materials, such as piezoelectrics, for sensing and actuation purposes [18]. The integration of structural dynamics is a pivotal focus, offering avenues for applications in structural health monitoring, energy harvesting, crashworthiness, and de-icing mechanisms. While this body of research may not directly involve CNNs, ANNs, or SVMs, it sets the stage for a comprehensive understanding of adaptive structures within aerospace vehicles. The emphasis on structural dynamics and the incorporation of smart materials illustrates the broader strategies employed to enhance the overall adaptability and efficiency of aircraft structures. The research findings underscore the dynamic landscape of utilizing CNNs, ANNs, and SVMs in the context of structural adaptive aircraft. From adaptive neural network-based flight systems addressing various control and monitoring aspects to the revolutionary application of CNNs for impact detection and characterization in composite structures, these technologies hold immense promise for the aerospace industry. The exploration of adaptive structures and materials further enriches the landscape, showcasing a commitment to advancing technologies that enhance aircraft performance, safety, and adaptability [17]. As research in this field progresses, the integration of machine learning techniques into the aerospace domain is poised to usher in a new era of intelligent, responsive, and resilient aircraft structures.

4.3 PROPOSAL METHOD

The Aircraft structural adaptivity, the ability of an aircraft's structure to dynamically change its shape, properties, or configurations in response to varying conditions, offers a range of benefits that positively impact performance, efficiency, and safety. Adaptive structures allow for real-time adjustments to the aircraft's shape, optimizing aerodynamic performance based on specific flight conditions [8]. This adaptability reduces drag, improves lift-to-drag ratios, and enhances overall aerodynamic efficiency. The ability to dynamically modify wing profiles, control surfaces, or other structural elements contributes to fuel savings and extended operational range. Structural adaptivity enables aircraft to optimize their configuration for different phases of flight, leading to improved maneuverability. By adjusting wing shape or control surfaces based on current requirements, the aircraft can respond more effectively to changes in altitude, speed, or direction. This benefits both military and commercial aircraft in various operational

scenarios. Adaptive structures allow for precise control of load distribution on the wings and other structural components. This capability is particularly valuable during different phases of flight, such as takeoff, landing, and cruising. Optimizing load distribution contributes to improved structural integrity, reduced stress on components, and enhanced overall safety.

The ability to dynamically adapt the structure based on operational requirements can lead to opportunities for weight reduction. Traditional fixed structures may be overdesigned to handle worst-case scenarios, resulting in unnecessary weight. Adaptive structures enable a more tailored and efficient distribution of materials, potentially reducing the overall weight of the aircraft. Structural adaptivity contributes to increased safety through various mechanisms. For instance, real-time impact detection and response systems can be integrated into adaptive structures, allowing the aircraft to dynamically adjust to mitigate damage caused by impacts or other structural stresses. This proactive approach enhances the aircraft's ability to withstand unforeseen events, improving overall safety. Adaptive structures can be designed to respond to external factors, such as turbulence or gusts, by adjusting the aircraft's configuration to optimize ride quality. This not only enhances passenger comfort but also contributes to the longevity of structural components by minimizing the effects of external forces. Adaptive structures can be optimized for cruise conditions, contributing to improved efficiency during most of the flight. By dynamically adjusting wing profiles or other features, the aircraft can maintain optimal performance levels, reducing fuel consumption and increasing overall cruise efficiency.

Adaptive structures can also respond to external factors, such as turbulence or gusts, by adjusting the aircraft's configuration to optimize ride quality. This not only enhances passenger comfort but also contributes to the longevity of structural components by minimizing the effects of external forces. Optimizing adaptive structures for cruise conditions contributes to improved efficiency during most of the flight. Dynamic adjustments to wing profiles or other features allow the aircraft to maintain optimal performance levels, reducing fuel consumption and increasing overall cruise efficiency. Continuous monitoring allows for early detection of potential issues, facilitating proactive maintenance and minimizing the risk of unexpected structural failures. The overarching objective of adaptive structures is to enhance aerodynamic efficiency, decrease energy consumption, and improve overall aircraft performance. The influence of adaptive structures on an aircraft's weight is multifaceted. Incorporating adaptive structures and multifunctional materials, including compliant skins and designs that are lightweight, stiff, and robust, contributes to decreasing the overall weight of the aircraft. By facilitating the design of lighter and more efficient structural components, adaptive structures significantly contribute to the overall reduction in aircraft weight, benefiting fuel efficiency and overall performance.

Adaptive structures often incorporate advanced sensing technologies for real-time monitoring of structural health. This continuous monitoring allows for early detection of potential issues, facilitating proactive maintenance and minimizing the risk of unexpected structural failures.

Some adaptive structures can be designed to harvest energy from ambient sources, such as vibrations or deformations during flight. Aircraft with adaptive structures can be designed with greater versatility to handle a broader range of missions or operational conditions. This adaptability is particularly valuable in military applications where aircraft may need to perform diverse roles, from surveillance to combat, with the ability to dynamically adjust their configurations. In summary, aircraft structural adaptivity brings a host of benefits, ranging from improved aerodynamic efficiency and maneuverability to enhanced safety and energy efficiency. As research and development in this field continues, the potential for even more advanced adaptive structures and their applications in future aircraft design remains promising.

Developing a structurally adaptive aircraft represents a multifaceted endeavor that requires the seamless integration of CNNs into both the design and control systems of the aircraft. The process begins with a precise definition of the objectives, with considerations given to aerodynamic optimization, load balancing, and damage detection. The ensuing steps involve the strategic placement of sensors throughout the aircraft, encompassing strain gauges, accelerometers, and other pertinent devices to facilitate real-time data acquisition. The collected sensor data then undergoes meticulous pre-processing, including normalization, filtering, and conversion into a format suitable for neural network training and subsequent inference.

A critical facet of the adaptive aircraft development lies in the design of a CNN architecture tailored to the specificities of the acquired sensor data and the overarching objectives of the adaptive system. This architecture typically incorporates convolutional layers for feature extraction, pooling layers for down-sampling, and fully connected layers for decision-making. The next phase involves the creation of a comprehensive dataset that includes labeled examples of various structural conditions and the corresponding adaptive responses. Through the iterative process of back propagation and optimization algorithms, the CNN learns the intricate relationships between the input data and the desired structural adaptations.

Having trained the CNN effectively, the integration process with the aircraft's control system ensues. This integration is a pivotal juncture where algorithms are devised to interpret the CNN's outputs and generate control signals that will govern the behavior of the adaptive components. These components, which may include shape-changing surfaces or control surfaces, are then equipped with actuators capable of translating the control signals into tangible adjustments in real time. The efficacy of this integration hinges on the responsiveness and precision of these actuators. After the integration, the adaptive aircraft undergoes rigorous testing and validation

Figure 4.5 Crafting tomorrow's skies with pioneering architectures and systemic elegance

in controlled environments. This entails subjecting the aircraft to an array of simulated scenarios that span diverse flight conditions, structural loads, and potential damage scenarios. The objective is to assess the performance and reliability of the adaptive system under varying circumstances.

Throughout this testing phase, adjustments are made, and the CNN and control algorithms are fine-tuned to enhance efficiency, responsiveness, and overall effectiveness. Continuous optimization efforts are essential to refine the adaptive system further. This involves ongoing adjustments based on performance feedback from testing, ensuring the adaptability of the aircraft is consistently improving. Moreover, the optimization process aims to strike a balance between efficiency and reliability, with an overarching goal of achieving optimal performance in real-world operational conditions.

As the development progresses, paramount attention must be given to safety and certification considerations. The adaptive system must adhere to stringent safety regulations and certification standards within the aerospace industry. This involves thorough scrutiny of the system's design, functionality, and reliability to ensure it meets the necessary criteria for safe operation. The certification process is integral to gaining regulatory approval for the deployment of the adaptive aircraft in real-world aviation scenarios. Interdisciplinary collaboration is a fundamental aspect of the

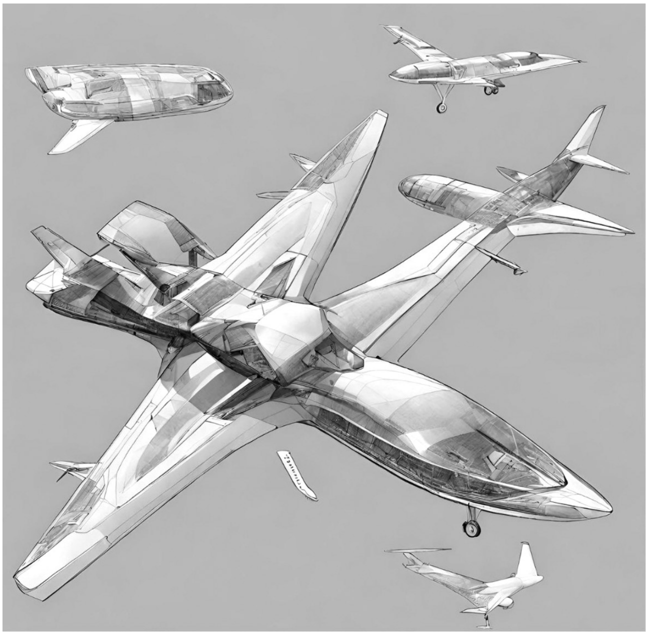

Figure 4.6 Mach Maverick: forging the future of aerial dominance through trailblazing designs for fighter jet fortitude

Table 4.1 The features against their ranges for structural adaptation

Feature	*Range for Structural Adaptation*
Strain (e.g., wing)	0–1000 microstrains
Acceleration	0–5 m/s^2
Load Distribution	0–100% (normalized)
Aerodynamic Parameters	Airspeed: 0–300 knots Angle of Attack: −10–10° Sideslip Angle: −5–5°
Temperature	−50–70°C
Vibration	0–10 Hz
Pressure (Altitude)	0–40,000 feet
Load Factor	0–2 (normalized load)
GPS Data	Latitude: −90–90° Longitude: −180–180° Altitude: 0–40,000 feet
Health Monitoring	Fatigue: 0–100% Crack Detection: Binary (0 or 1)
Control Surface Data	Positions: −30–30° (normalized)

entire development process. Aerospace engineers bring their expertise in aircraft design, structural analysis, and aerodynamics, while control systems experts contribute their knowledge in developing algorithms for real-time decision-making. Simultaneously, accelerometer readings emerge as indispensable features, capturing the aircraft's acceleration and vibrations. Rapid fluctuations in acceleration can serve as early indicators of disturbances, turbulence, or structural damage, providing the adaptive system with crucial information for prompt adjustments. Machine learning specialists play a crucial role in designing, training, and optimizing the CNN to effectively process and interpret the sensor data.

The creation of a structurally adaptive aircraft utilizing CNNs demands a holistic approach that encompasses the integration of sensors, actuators, and sophisticated control systems. From defining objectives and sensor integration to CNN training, system integration, and rigorous testing, each step plays a vital role in ensuring the effectiveness, safety, and reliability of the adaptive aircraft. The continuous cycle of optimization and adherence to safety standards underscores the complexity and precision required in this ground-breaking endeavor, highlighting the importance of collaboration across diverse fields of expertise. Developing a structurally adaptive aircraft necessitates a judicious selection of features that encapsulate critical aspects of the aircraft's structural health, performance, and the dynamic interplay between the aircraft and its environment. These features serve as the foundation for monitoring and decision-making processes, allowing the adaptive system to respond dynamically to varying conditions. One paramount category of features involves the measurement of strain in different components of the aircraft using strain gauges. These devices offer insights into the deformation or strain experienced by the aircraft's structure, enabling the detection of potential issues related to structural integrity and load distribution.

Load distribution, another pivotal parameter, is monitored through load sensors or load cells strategically placed to measure forces acting on various components. Understanding how loads are distributed across the aircraft is fundamental for optimizing performance and ensuring that structural elements bear loads within their designated capacities. Aerodynamic parameters constitute a vital set of features, including airspeed, angle of attack, and sideslip angle. These parameters offer a comprehensive view of the aircraft's aerodynamic behavior, facilitating real-time adjustments based on the evolving flight conditions. In an adaptive aircraft, the ability to dynamically respond to changes in aerodynamic parameters is paramount for optimizing performance and maintaining stability. Temperature and thermal stress are critical factors influencing structural adaptability. Features related to temperature provide insights into the thermal environment the aircraft encounters. Thermal stress, arising from temperature differentials, can impact structural integrity, necessitating adaptive measures to account for thermal expansion and contraction. Vibration analysis features

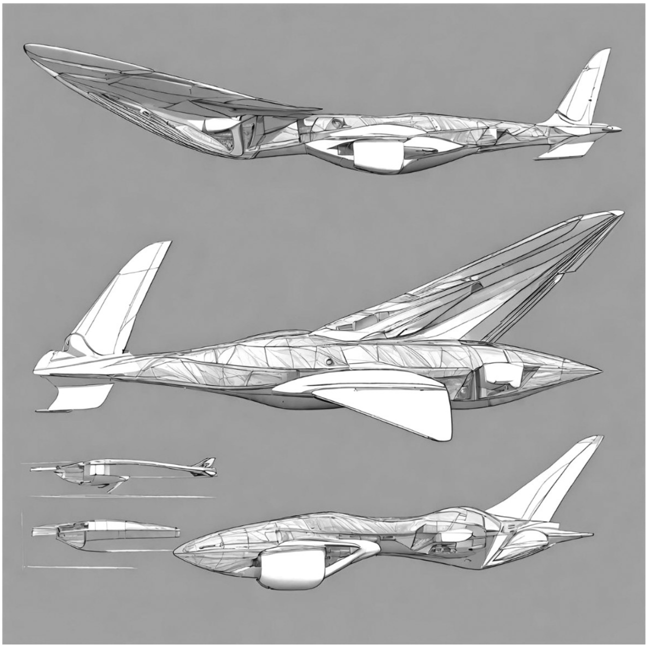

Figure 4.7 Whispers of the wind frame: unraveling the mystical blueprint for crafting celestial bodies – the artistry of airframe alchemy

contribute to the detection of abnormal vibrations or resonance frequencies, crucial for identifying potential structural issues. Vibration sensors strategically placed on the aircraft capture data that aids in assessing the overall health of the structure and mitigating potential risks associated with excessive vibrations.

Pressure sensors represent a key feature set for monitoring changes in atmospheric pressure, particularly at different altitudes. These changes directly influence the aircraft's structural dynamics, and real-time adjustments can be made to optimize performance and enhance safety. Load factor, another essential parameter, gauges the load experienced by the aircraft in comparison to its weight. Monitoring load factor provides valuable insights into structural loads during various maneuvers, enabling the adaptive system to respond appropriately to dynamic flying conditions. Integrating GPS data into the feature set offers information about the aircraft's position, velocity, and altitude. Changes in altitude or velocity can impact the structural dynamics, and GPS data aids in adjusting the adaptive system to accommodate variations in flight parameters. In addition to physical parameters, health monitoring sensors constitute a critical feature category. These sensors assess the condition of crucial components, offering data on fatigue, cracks, or corrosion. Such information is integral

for predictive maintenance and preemptive actions to ensure the aircraft's structural health over time. Furthermore, incorporating data from control surfaces, including elevators, ailerons, and rudders, enhances the feature set by providing real-time information about the positions and movements of these surfaces.

This data is invaluable for understanding and adapting to aerodynamic conditions, especially during flight maneuvers. Adjusting wing shape or control surfaces in response to current requirements allows the aircraft to respond more effectively to changes in altitude, speed, or direction. This flexibility is advantageous for both military and commercial aircraft across various operational scenarios. Additionally, adaptive structures facilitate precise control of load distribution on wings and other structural components. This capability is particularly valuable during different flight phases, such as takeoff, landing, and cruising. Optimizing load distribution contributes to improved structural integrity, reduced stress on components, and enhanced overall safety. The ability to dynamically adapt the structure based on operational requirements presents opportunities for weight reduction. Traditional fixed structures may be overdesigned to handle worst-case scenarios, resulting in unnecessary weight. Adaptive structures enable a more tailored and efficient distribution of materials, potentially reducing the overall weight of the aircraft. Safety is further enhanced through adaptive structures by incorporating real-time impact detection and response systems. These systems allow the aircraft to dynamically adjust to mitigate damage caused by impacts or other structural stresses, improving the aircraft's ability to withstand unforeseen events.

The chosen features collectively form a comprehensive monitoring system, capturing the intricacies of the aircraft's interactions with its environment and the structural responses to varying conditions. This rich feature set serves as the input for advanced machine learning techniques, particularly CNNs, which excel in processing complex spatial data. CNNs can analyze and interpret the intricate relationships within the feature data, facilitating informed decision-making for structural adaptation [5]. By leveraging the power of machine learning, the adaptive system can learn patterns, recognize anomalies, and dynamically adjust the aircraft's structure based on real-time feedback from the monitored features. The integration of these features into the adaptive aircraft's system exemplifies a holistic approach, where the synergy between aerospace engineering, control systems expertise, and machine learning proficiency is essential. The features selected align with the specific goals of the adaptive system, whether it be optimizing aerodynamics, detecting damage, or ensuring structural integrity. Moreover, the adaptability of the aircraft is contingent on the continuous refinement and expansion of the feature set, as advancements in sensor technology and data processing techniques offer new opportunities for enhancing the adaptive capabilities of the aircraft.

In conclusion, the process of selecting features for a structurally adaptive aircraft involves a meticulous consideration of the aircraft's structural dynamics, environmental influences, and performance requirements. The chosen features collectively contribute to a sophisticated monitoring system, enabling the adaptive aircraft to respond dynamically to changing conditions. This adaptive capability is further augmented by the application of machine learning techniques, exemplified by convolutional neural networks, which play a pivotal role in processing and interpreting the complex relationships inherent in the feature data. The seamless integration of these features and machine learning capabilities represents a pioneering frontier in aerospace engineering, marking a paradigm shift toward intelligent and adaptable aircraft systems. Creating a structurally adaptive aircraft utilizing SVMs involves a meticulous process of classification that enables the determination of the aircraft's structural condition based on sensor data. This approach offers a practical means of assessing and responding to changes in the aircraft's health, optimizing safety and maintenance practices. The journey begins with the definition of distinct classes that represent different structural conditions, such as "Healthy," "Damaged," or "Critical." The classification task relies on SVMs, a supervised machine learning algorithm capable of learning complex decision boundaries, making it well suited for discerning patterns within sensor data.

In the integration phase, a diverse array of sensors is strategically embedded throughout the aircraft, including strain gauges, accelerometers, and temperature sensors. These sensors serve as the primary data sources, capturing information indicative of the aircraft's structural integrity. The collected data is then subjected to pre-processing steps, encompassing normalization and scaling, ensuring uniformity, and facilitating meaningful input for the SVM model. A crucial step involves the division of the dataset into training and testing sets, laying the foundation for the model's learning process. Feature selection follows, where relevant features are identified from the sensor data. These features must encapsulate information critical for distinguishing between different structural conditions. With the features in place, the SVM model is trained using the labeled dataset. The scikit-learn library in Python provides an efficient implementation for Support Vector Classification (SVC), allowing the selection of appropriate kernel functions, such as "linear" or "rbf," depending on the characteristics of the data and the classification problem.

Once trained, the SVM model undergoes validation and evaluation using the testing set. Performance metrics, including accuracy, precision, recall, and the F1-score, offer insights into the model's efficacy in correctly classifying instances into their respective structural conditions. The confusion matrix further illuminates the model's ability to make accurate predictions. This evaluative phase is crucial in gauging the SVM model's reliability in real-world scenarios. Interpreting the SVM model's decision boundaries and support vectors provides a nuanced understanding of how the algorithm

distinguishes between various structural conditions. This comprehension forms the basis for integrating the trained SVM model into the aircraft's control system. In real-time, the SVM model processes sensor data, predicting the structural condition of the aircraft. The integration extends to the implementation of actuators or adaptive components, enabling the aircraft to make instantaneous adjustments based on the perceived structural condition. This adaptive response, rooted in machine learning predictions, enhances the overall safety and performance of the aircraft.

Continuous monitoring and maintenance procedures are established based on SVM predictions. Regular assessments of the aircraft's structural condition ensure timely interventions, mitigating potential issues before they escalate [9]. The SVM-based adaptive system offers a proactive approach to maintenance, contributing to the overall longevity and reliability of the aircraft. Ensuring compliance with safety regulations and certification standards is paramount throughout the development and deployment of the adaptive system. Rigorous testing, validation, and adherence to industry standards solidify the aircraft's readiness for real-world application. In essence, the application of SVM for determining the structural condition of an aircraft epitomizes a synergy between machine learning, sensor technology, and aerospace engineering. The resulting adaptive system demonstrates the potential to revolutionize maintenance practices, fostering a safer and more efficient operational environment for aircraft in dynamic and demanding conditions in the intricate realm of structural adaptation for aircraft, a multitude of features intricately dictate the dynamic responses of the aircraft to varying conditions. Each feature encapsulates vital aspects of the aircraft's structural health, necessitating vigilant monitoring and adaptive measures to ensure optimal performance, safety, and longevity.

The drive toward lighter aircraft is not only propelled by the quest for enhanced performance but also by the imperative to reduce fuel consumption and minimize environmental impact. Adaptive structures play a pivotal role in achieving these objectives by enabling a more judicious use of materials and fostering innovations in design. Furthermore, the evolution of adaptive structures extends into the realm of materials science. The incorporation of multifunctional materials, such as compliant skins, and the pursuit of designs that are simultaneously lightweight, stiff, and robust, represent a paradigm shift in how aircraft are constructed. This departure from traditional fixed structures toward adaptive, lightweight alternatives is a testament to the industry's commitment to pushing the boundaries of what is technologically achievable and environmentally sustainable. Advancements in adaptive composite structures, utilizing concepts like structural instability and buckling-driven design, represent a concerted effort to not only make aircraft lighter but also to enhance the overall efficiency of composite aerospace structures. The fusion of material science and adaptive technology is poised to redefine the parameters of what is considered possible in aircraft design, paving the way for a new era of aerospace innovation.

Starting with the temperature of the fuselage, this critical feature plays a pivotal role in the structural adaptation process. The temperature directly influences the material properties of the aircraft, particularly in composite structures. Extremes in temperature, whether scorching heat or freezing cold, can induce thermal expansion or contraction, potentially compromising the structural integrity of the fuselage. As such, monitoring the temperature and dynamically adapting the aircraft's structure is imperative to withstand the diverse environmental conditions encountered during flight. Moving to the angle of attack, another pivotal feature in structural adaptation, its significance lies in influencing the aerodynamic forces acting on the aircraft. The angle of attack is the orientation of the aircraft concerning the oncoming air, and changes in this angle can impact the lift and drag forces. Excessive angles may lead to structural issues, affecting stability and potentially causing structural damage. Hence, adapting the structure based on the angle of attack ensures optimal aerodynamic performance and structural stability during various flight conditions. Vertical acceleration emerges as a crucial feature representing forces acting in the up-down direction on the aircraft. During flight, vertical accelerations can result from maneuvers, turbulence, or other external factors. Monitoring these accelerations becomes paramount to prevent structural fatigue and ensure the aircraft structure can withstand the dynamic forces encountered during flight. By adapting the structure based on observed vertical accelerations, potential structural issues can be addressed proactively, contributing to enhanced safety and structural resilience. Structural vibration, as another feature in the adaptation paradigm, emanates from various sources, including engine vibrations, turbulence, or aerodynamic forces. Excessive vibrations, if left unaddressed, can lead to fatigue, and compromise the structural integrity of the aircraft over time. Therefore, monitoring structural vibrations and dynamically adapting the aircraft's structure are integral to mitigating potential damage, enhancing overall safety, and prolonging the operational life of the aircraft. Finally, altitude, a feature intertwined with aerodynamic performance, holds a substantial role in the structural adaptation landscape. Altitude variations impact air pressure and density, influencing the aerodynamic loads on the aircraft. Adapting to changes in altitude ensures that the aircraft structure can efficiently navigate different flight phases, adjusting to the aerodynamic forces associated with ascents or descents. By dynamically adapting the structure to altitude variations, the aircraft optimizes its performance across a spectrum of operating conditions [4]. In essence, these features collectively weave the intricate fabric of structural adaptability in modern aircraft. The interplay of temperature, angle of attack, vertical acceleration, structural vibration, and altitude underscores the multidimensional approach required for comprehensive structural health monitoring and adaptation. The fusion of these features into a cohesive adaptive system allows the aircraft to respond effectively to the myriad environmental and operational challenges encountered during its lifespan. In this example, Strain (Wing) represents the deformation

or strain in the aircraft's wing. The range is set from 0 to 500 microstrains, indicating the acceptable level of strain that the wing can undergo before structural adaptation is required. Acceleration represents the acceleration experienced by the aircraft. The range is set from 0 to 10 m/s^2, accounting for both positive and negative accelerations that may trigger structural adaptation. Load Distribution (Left Wing and Right Wing) represents the distribution of loads between the left and right wings. The range is set from 20% to 50%, indicating the acceptable range for the load distribution on each wing. This may be crucial for maintaining balance and structural integrity during flight.

In conclusion, the integration of a structurally adaptive system for aircraft represents a ground-breaking fusion of aerospace engineering, sensor technology, and machine learning. The meticulously selected features, ranging from atmospheric parameters to health monitoring sensors, create a comprehensive monitoring system essential for real-time structural adaptation. The interplay of temperature, angle of attack, acceleration, vibration, and altitude encapsulates the multidimensional nature of structural adaptation, ensuring the aircraft's resilience to diverse environmental challenges. The integration of CNN predictions into the control system enables instantaneous adjustments, fostering a proactive approach to maintenance and prolonging the aircraft's operational life. This holistic approach, backed by material science insights and performance metrics, marks a paradigm shift in aerospace engineering, promising intelligent, adaptable, and safer aircraft systems for the dynamic demands of modern aviation.

4.4 RESULTS AND DISCUSSION

Temperature (Fuselage): Represents the temperature range that the aircraft fuselage can withstand. The range is set from −40°C to 80°C, covering potential temperature variations during flight or environmental changes. Angle of Attack: Reflects the angle between the aircraft's longitudinal axis and the oncoming air. The range is set from -5° to 15°, indicating the acceptable angles at which the aircraft can operate without compromising structural integrity. Vertical Acceleration: Represents the vertical acceleration experienced by the aircraft. The range is set from −5 m/s^2 to 5 m/s^2, accounting for both upward and downward accelerations that may impact the aircraft structure. Structural Vibration: Indicates the frequency of structural vibrations experienced by the aircraft. The range is set from 0 to 20 Hz, encompassing the frequencies relevant for monitoring potential structural issues due to vibrations. Altitude: Represents the aircraft's altitude above sea level. The range is set from 0 to 40,000 feet, considering variations in altitude during different phases of flight and the corresponding impact on structural conditions. This demonstrates the diversity of features that can be monitored for structural adaptation, each with its specific range

Table 4.2 Corelation of different features and their variations

Material	*Elasticity Modulus*	*Density*	*Yield Strength*	*Fatigue*
Carbon Fiber Composite	75,000 GPa	1.6 g/cm³	600 MPa	10^7 cycles
Aluminum Alloy	70,000 GPa	2.7 g/cm³	300 MPa	10^6 cycles
Titanium Alloy	110,000 GPa	4.5 g/cm³	900 MPa	10^8 cycles

Table 4.3 Approximation of management of different models of aircrafts

Aircraft Model	*Maximum Load Reduction (%)*	*System Response Time (s)*	*Power Consumption (kW)*
Model A	92	0.2	120
Model B	98	0.3	150
Model C	95	0.1	100

Table 4.4 Required parameters and their description

Wing Section	*Number of Sensors*	*Sensor Types*
Leading Edge	10	Strain Gauges, Temperature Sensors
Trailing Edge	8	Accelerometers, Pressure Sensors
Wing Spar	12	Load Cells, Deflection Sensors
Fuselage Integration	15	Gyroscopes, Vibration Sensors

Table 4.5 Assessing features in the context of their applicable ranges for structural adaptation

Feature	*Range for Structural Adaptation*
Strain (Wing)	0500 microstrains
Acceleration	0–10 m/s²
Load Distribution (Left Wing)	20–50% (normalized)
Load Distribution (Right Wing)	20–50% (normalized)

based on the unique characteristics and requirements of the aircraft. Again, it's crucial to tailor these values to the specific aircraft model, considering factors such as materials, design constraints, and safety considerations.

Fatigue (Fuselage): Monitors the health of the fuselage material, providing a percentage indicating the extent of fatigue. Adapting the structure based on fatigue levels ensures that the aircraft remains robust and resilient over time. Corrosion (Tail Section): Tracks the level of corrosion in the tail section. The range reflects the health percentage, and structural adaptation is initiated based on corrosion levels to prevent further

Table 4.6 Exploring how features align with their optimal ranges to facilitate creative structural adaptation

Feature	*Range for Structural Adaptation*
Temperature (Fuselage)	−40°C to 80°C
Angle of Attack	−5°–15°
Vertical Acceleration	−5 m/s² to 5 m/s²
Structural Vibration	0–20 Hz (frequency)
Altitude	0–40,000 feet

Table 4.7 Analyzing features in relation to their respective ranges for structural adaptation

Feature	*Range for Structural Adaptation*
Fatigue (Fuselage)	0–100% (health percentage)
Corrosion (Tail Section)	0–30% (health percentage)
Composite Integrity (Wing)	Binary (0 or 1)
Crack Detection (Empennage)	Binary (0 or 1)

Table 4.8 Examining features within the confines of their prescribed ranges for the purpose of formal structural adaptation

Feature	*Range for Structural Adaptation*
Lift-to-Drag Ratio (L/D)	5–20
Wing Sweep Angle	0–30°
Airspeed (Cruise)	200–600 knots
Flap Deployment	Binary (0 or 1)

deterioration. Composite Integrity (Wing): A binary feature indicating the integrity of composite materials in the wings. Structural adaptation is triggered if any compromise in composite integrity is detected. Crack Detection (Empennage): A binary feature signaling the presence or absence of cracks in the empennage. Immediate structural adaptation is necessary if cracks are detected to prevent structural failure. ,

Lift-to-Drag Ratio (L/D): Reflects the efficiency of aerodynamic performance. Adapting the structure based on L/D ratio ensures optimal lift and drag forces during different flight conditions.

Wing Sweep Angle: Monitors the angle of wing sweep, influencing aerodynamic characteristics. Structural adaptation based on wing sweep angles is crucial for stability and performance.

Airspeed (Cruise): Defines the aircraft's cruise speed. Adapting the structure based on airspeed variations ensures structural integrity and aerodynamic efficiency during cruise phases.

Table 4.9 Attributes and their description for the necessity and consideration

Feature	*Description*	*Benefits*
Variable Sweep Angle	Change wing sweep angle during flight	Enhanced Maneuverability at different speeds
Morphing Wing Shape	Adapt wing shape for optimal lift and drag	Improved aerodynamic efficiency
Aeroelastic Tailoring	Optimize wing structure for aerodynamic performance	Increased structural efficiency
Smart Materials	Materials that can change properties based on stimuli	Dynamic adjustments based on conditions
Load Alleviation System	Redistribute loads on the wing for stress reduction	Prolongs wing lifespan, reduces maintenance
Embedded Sensors	Monitor wing conditions and external factors	Real-time data for adaptive adjustments
Active Flow Control	Use actuators to manipulate airflow over the wing	Improves lift, reduces drag
Energy Harvesting	Harness energy from aerodynamic forces or vibrations	Power sensors or other systems

Table 4.10 Minimum–maximum ranges for the adapted features

Feature	*Parameter*	*Value*
Variable Sweep Angle	Maximum Sweep Angle	25
Morphing Wing Shape	Aspect Ratio Change Range	1.5
Aeroelastic Tailoring	Elasticity Modulus	80,000
Smart Materials Integration	Actuation Response Time	0.3
Load alleviation system	Load Redistribution Efficiency	95
Embedded Sensors	Sensor Density	20
Active Flow Control	Actuator Power Consumption	150
Energy Harvesting	Harvested Energy per Flight Hour	8

Table 4.11 Accuracy scores against the algorithms

Algorithm	*Accuracy Score (%)*
Convolutional Neural Networks	88
K-Nearest Neighbors	74
Support Vector Machines	67
Artificial Neural Networks	81

Flap Deployment: A binary feature indicating whether flaps are deployed. Structural adaptation is initiated when flaps are deployed to accommodate changes in lift and drag during takeoff or landing. , , , ,

Table 4.12 Error rates along with the error rates

Algorithm	*Error Rate (%)*
Convolutional Neural Networks	12
K-Nearest Neighbors	26
Support Vector Machines	33
Artificial Neural Networks	19

Table 4.13 Performance measures of their respective algorithms

Precision	*Specificity*	*Sensitivity*	*F1 Score*	*Algorithm*
76	62	73	71	Support Vector Machines
54	60	55	58	K-Nearest Neighbors
85	69	68	81	Convolutional Neural Networks
65	64	59	66	Artificial Neural Networks

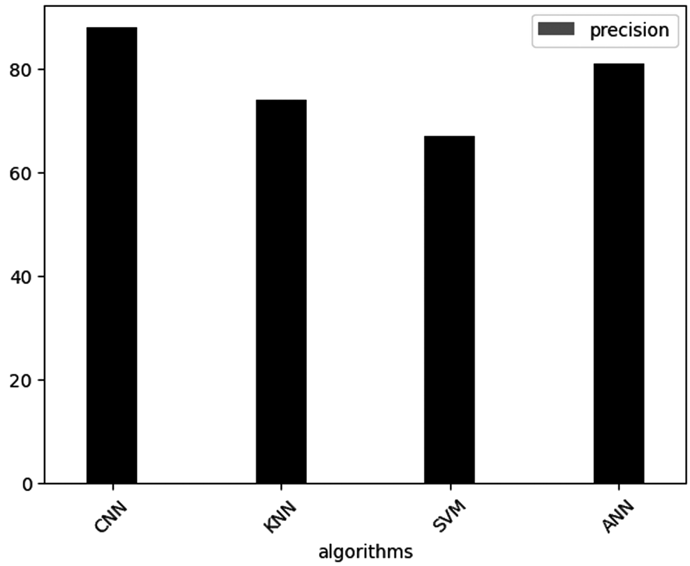

Figure 4.8 Accuracy scores against the algorithms

4.5 CONCLUSION

The concept of aircraft structural adaptivity, denoting the capacity of an aircraft's structure to dynamically alter its shape, properties, or configurations in response to varying conditions, offers a myriad of advantages that significantly impact performance, efficiency, and safety. One of the

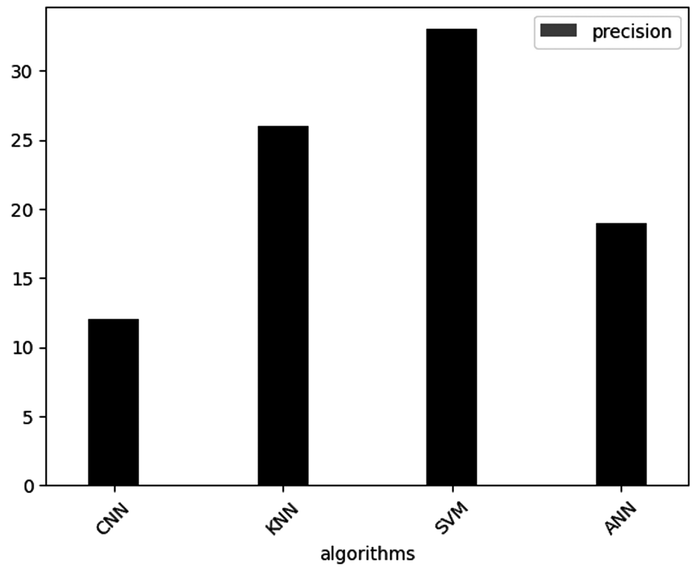

Figure 4.9 Error rates against the algorithms

key benefits of adaptive structures in aircraft lies in their ability to make real-time adjustments to the aircraft's shape, optimizing aerodynamic performance based on specific flight conditions. This adaptability translates into reduced drag, improved lift-to-drag ratios, and enhanced overall aerodynamic efficiency. ,

The application of CNNs for aircraft detection in remote sensing images signifies a convergence of cutting-edge technologies. This not only enhances surveillance and monitoring capabilities but also introduces a new dimension to the way aircraft are identified and tracked, with implications for security, border control, and environmental monitoring. The adaptability of CNNs in processing and understanding visual data is a testament to their versatility. Beyond aircraft detection, their hierarchical learning approach holds promise for addressing other challenges within the aerospace industry, such as predictive maintenance, fault detection, and even autonomous flight systems. The marriage of adaptive structures and artificial intelligence represents a synergy that could redefine the landscape of aviation, opening avenues for unprecedented levels of efficiency, safety, and autonomy. In conclusion, the incorporation of adaptive structures in aircraft is not merely a technological upgrade but a fundamental shift in how we conceptualize and engineer aerospace systems. It is a journey toward more sustainable, efficient, and technologically advanced aviation. The ongoing advancements in materials science, coupled with the integration of artificial intelligence, underscore the dynamic nature of this evolution. As

these technologies continue to mature and converge, the aerospace industry is poised for a transformative era where adaptive structures and artificial intelligence collaborate to redefine the possibilities of flight.

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Chapter 5

Industry 6.0 in transportation systems

Exploring the Simulated futures of automated bus fleet integration with alternative fuel infrastructures in closed sociotechnical environments

Ifezue Obiako, Kari Lippert, Sean Walker, and Robert Cloutier

5.1 INTRODUCTION

Automated vehicles or AVs have long captured the imagination and wonder of society for well over half a century due to their ability to provide users freedom from the complex daily tasks of driving. Beyond mere science fiction, AVs are vehicles composed of various sensors, an on-board unit (OBU), and communication devices that when used in tandem, enable perception, localization, trajectory planning, decision-making, and actuation [1]. This process imparts a sense of environmental and situational awareness to the vehicle and its behavior [2].

Automated capabilities such as perception, decision making, and actuation have already become the quintessential building blocks of advanced driver-assistance systems (ADAS) that are pervasive features in current vehicle models. Many of these ADAS features can be observed through the evolutionary progression of the SAE automation levels which range from SAE Level 0 (no automation) to SAE Level 5 (full automation) [3]. With SAE Level 5, AVs possess the potential to reduce traffic congestion [4, 5], improve traffic safety [6, 7], reduce fuel consumption [8], transform urban typology of cities [9], incorporate new business models [11], and much more. Over the years these emergent capabilities have garnered interest from numerous automotive companies and suppliers, tech companies, institutions, and governmental agencies. This interest from various organizations has helped advance AV technology through extensive investments in research and development (R&D).

With these advantages AVs provide, there are also various systemic issues and concerns that need to be confronted before widespread adoption or deployment of AVs is undertaken. Some of these concerns pertain to the way 1) testing and development (T&D) of AVs are being conducted on

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public roads, and 2) the lack of critical emphasis towards the fueling infrastructure that will support AV operations.

Currently, the predominant form of testing of AVs is through large-scale testing. In some cases, T&D of AVs have been known to occur on public roads. Companies such as Google, Uber, and others have performed AV tests on public roadways. AVs are not fully accustomed to the nuances of driver, pedestrian, and cyclist behaviors (and vice versa) making them susceptible to accidents, increasing fear and distrust of AVs [12]. More sensible, and systemic deployment of AVs will be needed if trust and widespread adoption of AVs is expected to occur soon.

The public has shown widespread fear of automated cars (ACs), but a more positive attitude toward ABs being used as daily transporters [13] or slow people movers [14]. R&D efforts are mostly interested in private mobility applications rather than public mobility applications of AVs. This is a disconnect between the desires of the public and the research community. To align these interests and gain public trust of AV technology, ABs rather than ACs can be used as the gateway to further trust and adoption of AVs. In addition, there is also the overlooked issue regarding the assumption that AVs will be battery electric vehicles (BEVs). The assumption of using BEVs as AVs could be detrimental systemically because of two issues:

- **Supply chain issues** regarding the raw materials of the batteries of BEVs when economies of scale are considered. Conventional BEVs are powered by lithium-ion batteries that are composed of nickel and cobalt which are in limited quantity and are sensitive to geopolitical factors like fossil fuels [15] making could make their prices volatile in nature.
- **Environmental and human rights issues** with mining practices of extracting new lithium and cobalt [16–18].

To address these two major arenas, more integrative virtual testing of AVs and fueling technologies needs to be performed. Also, testing of these integrated technologies will need to be investigated in a more controlled and bounded environment to allow their behaviors, interactions, and corresponding impacts to be fully understood. The contribution of this chapter provides an outlet to address AB M&S gaps by assessing the level of effectiveness in integrating ABs with different fueling and charging infrastructure technologies in a bounded and scaled down sociotechnical environment – the University of South Alabama (USA) campus. A further contribution of this chapter is to glean insight into the possibilities that exist in integrating fueling/charging infrastructures and vehicle autonomies for entire bus fleet architectures.

The purpose of this chapter is to understand the systemic architecture implications of AB integration with alternative fueling and charging technologies within a closed sociotechnical environment using an M&S approach. This was accomplished by addressing the following hypothesis:

- ***Hypothesis 1:*** *Using ABs will enhance transportation performance within CSE.*
- ***Hypothesis 2:*** *AB integration with natural gas, propane, hydrogen, biodiesel, and electric fueling and charging infrastructures does not provide equally reliable transportation within CSE.*
- ***Hypothesis 3:*** *Alternative or blended AB/fleet combinations enhances transportation performance within CSE.*

The rest of this chapter was coordinated as follows: section 5.2 provides a review of the state of the art in M&S of ABs and its integration with different fueling and charging infrastructures. In sections 5.3 and 5.4, methodology and design of experiments (DoE) used to achieve the objectives of this chapter are specified. In Section 5.5 results from data analysis and hypothesis testing are presented, while results are also discussed in the latter stages of the sections. Concluding remarks and future work are posed in sections 5.6 and 5.7; respectively.

5.2 LITERATURE REVIEW

Within the existing body of AV M&S literature, AVs are often envisioned as cars utilized in future transport applications such as robotaxi services [19, 20], autonomous ridesharing [21–25] or private autonomous transport services [26]. Use cases of ACs in peer economies have showcased in various literature promising future outcomes such as potentially replacing private human-driven vehicles (HDVs) [27–29]. However, high levels of dependency on a single transportation modality can be damaging to the stability of the transportation ecosystem and their corresponding networks [5, 25, 30, 31]. Smith [32] suggests that emissions per mile could decrease, but daily emissions could increase as a result. Findings from [32], revealed that transportation modal diversity will reduce mobility-related emissions, traffic congestion, and transport times with AV integration in transportation spaces [10, 33].

Deprivation of public transportation can be avoided by incorporating AVs in mass transit as public buses. This is the idea behind ABs. The public has voiced a higher level of approval of using and eventually adopting ABs in existing transportation systems [13, 34, 35]. However, according to [36] trust in ABs decreases if no driver is present during AB operations. This adds further complexity in the trust and adoption of ABs. Conversely, [37] has implied the public is not ready for the use of shared AV taxis.

5.2.1 Modeling and simulation of automated buses with different alternative fueling infrastructures

Since AVs will spend little time idle or parked, vehicle fuel type and infrastructure will be crucial components of AB transport systems. Jing et al.

[40] showed there is a lack of M&S research in refueling/recharging AVs. Vosooghi et al. [41] have also performed M&S of AVs with an emphasis on charging location and charging types and their impact on shared autonomous electric vehicles (SAEV) performance. Zhang and Chen [42] investigated using an intelligent charging management framework for a SAEV fleet in the Puget Sound region of the United States.

Technical issues such as low driving range are a prominent weak point of using BEVs. Electric charging technologies like battery swapping technology/stations (BST/BSS) and wireless power transfer (WPT) can decrease driver anxiety about range and increase battery life. Studies [43–45] have shown by using a properly designed WPT network, an automated electric shuttle system can obtain infinite driving range, minimal recharge downtime, and battery size reduction. Ding et al. [46] integrated the use of autonomous mobility-on-demand fleet and BSS in New York City and were able to reduce refueling times of the EV fleet.

5.2.2 Modeling and simulation of automated buses in unique sociotechnical environments

AVs will be expected to operate in diverse operational environments. The built environment of cities offers various diverse environments with unique social behaviors. However, these complex social behaviors and norms could be perceived as unpredictable for AVs, and therefore, a risk to the public.

Woven in the fabric of built environments are localities that form part of the architectural landscape of cities. In this chapter, these special localities are referred to as CSE. It is in these enclaves that AV research, development and deployment can be explored, supporting genteel AV integration into transportation ecosystems [38, 47]. A CSE is a built ecosystem that has a relatively restrained and small flow of denizens, traffic, and services in and out of its internals relative to its environs. Examples of CSEs are university campuses, innovation districts, and military installations.

In terms of existing studies, two studies [38, 45] have used M&S to investigate the performance of AVs in CSEs. One study [38] investigated the impact and interaction of utilizing RoboShuttles within pedestrian flows in the Robert Bosch GmbH campus of Renningen, Germany. On the other hand, another study [45] examined the use of an autonomous shuttle with WPT technology in the National Renewable Energy Laboratory (NREL) campus.

5.2.3 Modeling and simulation of automated buses in different bus and fleet configurations

AB fleets can come in unique configurations composed of different bus types. Also, AB fleets can be comprised of buses with distinct autonomy levels to add more variety to bus fleet architecture. Dai et al. [48] have developed a

joint-optimized scheduling scheme for dispatching both ABs mini shuttles and HDBs in a hybridized bus fleet relative to dynamic demand. Results from this hybridized fleet configuration showed improvements in operating costs and passenger wait times.

From existing literature, three major gaps need to be addressed in M&S studies of ABs; they consist of: 1) inadequate simulation of ABs with various alternative fueling infrastructures, 2) insufficient simulation of ABs in environments aside from cities, and 3) a lack of simulation of ABs in distinct bus and fleet configurations. The aim of this work is to address all three of these gaps.

5.3 METHODOLOGY

The research approach utilized an M&S approach. In this approach, USA's JagTran system was the system of interest (SoI) with the USA campus being considered a CSE. The general methodology consisted of data collection of model inputs, model validation, experimentation, and data analysis.

5.3.1 Data collection of modeling and simulation Inputs

In data collection, datasets from various sources were obtained through a mixture of methods. There was a total of four data categories, with the categories consisting of: JagTran data, traffic flow data, AB data, and fueling/charging infrastructure data. All datasets from each of these data categories were input into the simulation tool known as the Simulation of Urban Mobility (SUMO). Figure 5.1 shows the data hierarchy of the M&S input data.

5.3.1.1 JagTran data

The JagTran bus system provides transportation service in the USA campus and immediate areas using a fleet of HDBs. These buses serve the campus through five routes: blue, green, yellow, orange, and red. In total, there are eight JagTran buses that are on all five bus routes. Each bus also uses an on-site diesel refueling station to satisfy fueling needs for each bus. Table 5.1 shows the attributes of the JagTran bus network which consists of the route length for each route, number of buses that service each route, and the number of bus stops on each designated route.

5.3.1.1.1 JagTran operations and specifications data

Datasets from JagTran operations and specifications were obtained through an elicitation process that consisted of questioning personnel from the

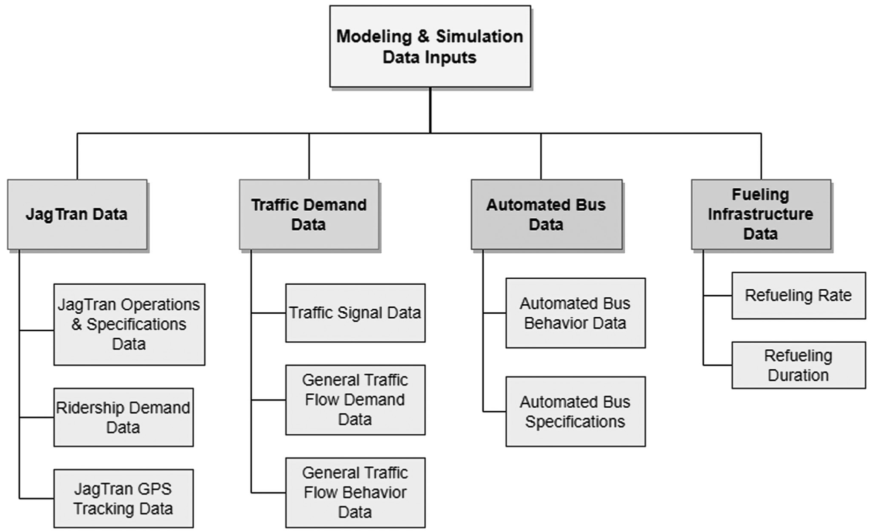

Figure 5.1 Hierarchy describing the categories of collected data

Table 5.1 Attributes of JagTran bus network

JagTran Bus Route Designation	*Bus Route Length*	*Number of Buses*	*Number of Bus Stops on Route*
Blue Route – km (miles)	4.12 (2.75)	2	7
Green Route – km (miles)	5.35 (3.40)	2	10
Yellow Route – km (miles)	5.14 (3.11)	2	6
Orange Route – km (miles)	2.99 (1.84)	1	6
Red Route – km (miles)	2.63 (1.86)	1	6

Transportation Services department at USA. From these conversations, specifications of the JagTran buses were obtained to be used in the M&S environment. Other sources were used as assumptions to fill in technical details not revealed in the interviews. Table 5.2 depicts the bus specifications and behavioral inputs assumed for the HDB bus agents in the simulation. Bus specifications in Table 5.2 were based on Ford E450 vehicle which is akin to the JagTran bus specification in terms of seating capacity, dimensions, and vehicle weight.

5.3.1.1.2 Data on ridership

Historical data on ridership demand from the Spring 2019 semester was used to simulate ridership demand in SUMO. This data was obtained from the USA Transportation Services department. The dataset consisted of

Table 5.2 Specifications used for modeling JagTran bus agents in simulation

Characteristic	*Value*
Bus Fuel Type	Diesel
Bus Fuel Capacity – gal (L)	30 (113.6)
Bus Seating Capacity	15
Vehicle Chassis	Ford E450
Bus Length – m (ft)	7.28 (23.88)
Bus Width – m (ft)	2.44 (8.01)
Bus Height – m (ft)	2.88 (9.45)
Bus Weight – kg (lbs.)	5262 kg (11578.7)

various data points of the number of persons boarding every hour. Data obtained consisted of hourly count data over a one-month period which was used in ridership variation analysis.

5.3.1.1.3 Data from GPS tracking

GPS trackers on JagTran buses record real-time bus location data. To promote efficient use of the JagTran system, this data updates JagTran Tracker, a mobile app. The GPS data includes vehicle speed, position data, heading, and time. The USA Computer Services department made this data available. Analysis of this data revealed the movement of JagTran buses around the campus and were converted for use in the simulated campus.

5.3.1.1.4 Behavior of buses

Behavioral attributes modeled in the simulation environment for the JagTran agents, assumed values from existing literature [39, 49–54] which consisted of vehicle variables such as acceleration, deceleration, minimum headway maintenance, and car following behavior. These values required external investigation as they were not provided through elicitation and were needed to impart realism within the model. Table 5.3 shows the behavior assumptions utilized in the simulation environment.

In Table 5.3, behavioral attributes such as headways were given large headways for vehicle and passenger ride comfort and safety. The Krauss car following model was used due to known parameters for the model. In the model, the sigma (Σ) parameter which represents driver imperfection, where 0 is perfect and 1 is imperfect, was assumed to be 0.5 because of the imperfections of human drivers. Tau (T), on the other hand, is indicative of the driver's reaction time which is assumed to be 2.5 seconds based on literature findings [52].

Kinematic-based behavioral attributes in Table 5.3 were also accompanied by bus schedules for each JagTran bus on their respective routes. Each

Table 5.3 HDB JagTran bus agent parameters

Behavioral Attribute	*Assumption*		
Acceleration – m/s^2 (ft/s^2)	1.19 (3.9)		
Deceleration – m/s^2 (ft/s^2)	−1.45 (−4.76)		
Max deceleration – m/s^2 (ft/s^2)	−2 (−6.56)		
Headway – m (ft)	4 (13.12)		
Car Following Model	Krauss Model	Σ	0.5
		T	2.5 sec.
Time to Load/per Passenger	$t_{boarding}$ + 0.5 sec. = **2.25 sec.**		

bus was assigned a starting bus stop. The bus schedule for HDBs exhibited varied wait times at stops along the route. These wait times were determined from the GPS data. JagTran bus stops for each individual bus can be seen in Table 5.4, while timetables for each bus route are provided in Figure 5.2.

In Table 5.4, bus stop id numbers are used to correspond to bus stops on each of the different JagTran bus routes which are aligned with each bus on the designated route. Each of the bus stops id numbers shown in Table 5.4 were implemented in Figure 5.2 with a bus schedule timeline to show the temporal progression of the buses as they moved throughout the campus environment. In Figure 5.2, the circled quantities are representative of the bus stop id numbers from Table 5.4, while quantities above the bus stop id number are the duration of time in seconds the bus spends at the stop. Quantities within the boxes that are not circled are the amount of time the bus is expected to spend in transit between bus stops.

5.3.1.2 Data from traffic light system

Traffic signal data consisted of observational data, both historical and actual observations, to determine the sequencing and timing at campus boundary intersections. Data was collected from 10 of the 11 intersections. Historical traffic signal data was obtained through the Mobile Department of Traffic Engineering (MDoTE).

Field observation data was obtained through on-site observations of the traffic light signal sequencing. Cameras were used to capture 90 minute-videos of traffic at the 10 intersections during morning (7:30–9:00 am) and evening (4:30–6:00 pm) peak periods. This data was used to compare actual observations to the timings provided by the MDoTE. By combining the two sets of data the logic for the simulated traffic lights was generated.

5.3.1.2.1 Traffic flow data

Traffic flow data consisted of collecting historical and field observation data. Again, historical data was obtained from the MDoTE and from the

Table 5.4 Bus stops and their identification (id) numbers relative to bus routes

Blue Route	*Bus 1*		*Bus 2*	
	ID	**Stop Name**	**ID**	**Stop Name**
	1	Grove Apartments	4	Student Center Circle
	2	Stadium Drive	5	Humanities South
	3	Gamma Connection	6	Delta Dorms
	4	Student Center Circle	7	Dining Hall West Bound
	5	Humanities South	1	Grove Apartments
	6	Delta Dorms	2	Stadium Dr.
	7	Dining Hall West Bound	3	Gamma Connection
Green Route	1	Grove Apartments	6	Delta
	8	Gravel Parking	7	Dining Hall West Bound
	9	Greek Row	1	Grove Apartments
	10	Dining Hall East Bound	8	Gravel Parking
	6	Delta Dorms	9	Greek Row
	11	Humanities North	10	Dining Hall East Bound
	12	Marx Library	6	Delta Dorms
	4	Student Center Circle	11	Humanities North
	6	Delta	12	Marx Library
	7	Dining Hall West Bound	4	Student Center Circle
Yellow Route	14	Student Center South	13	University Commons
	5	Humanities South	14	Student Center South
	15	Laidlaw Building	5	Humanities South
	16	Shelby Hall	15	Laidlaw Building
	17	Mitchell Center	16	Shelby Hall
	13	University Commons	17	Mitchell Center
Orange Route	4	Student Center Circle		
	18	Visual Arts Building		
	19	Administration Building		
	15	Laidlaw Building		
	16	Shelby Hall		
	20	Student Services Building		
Red Route	4	Student Center Circle		
	21	College of Medicine Building		
	22	Allied Health North Bound		
	23	Health Services Road Parking		
	24	Research Park		
	25	Allied Health South Bound		

Alabama Department of Transportation (ALDOT). MDoTE provided a limited amount of data for certain roadway segments surrounding the USA campus. To fill gaps in this data, ALDOT data was used.

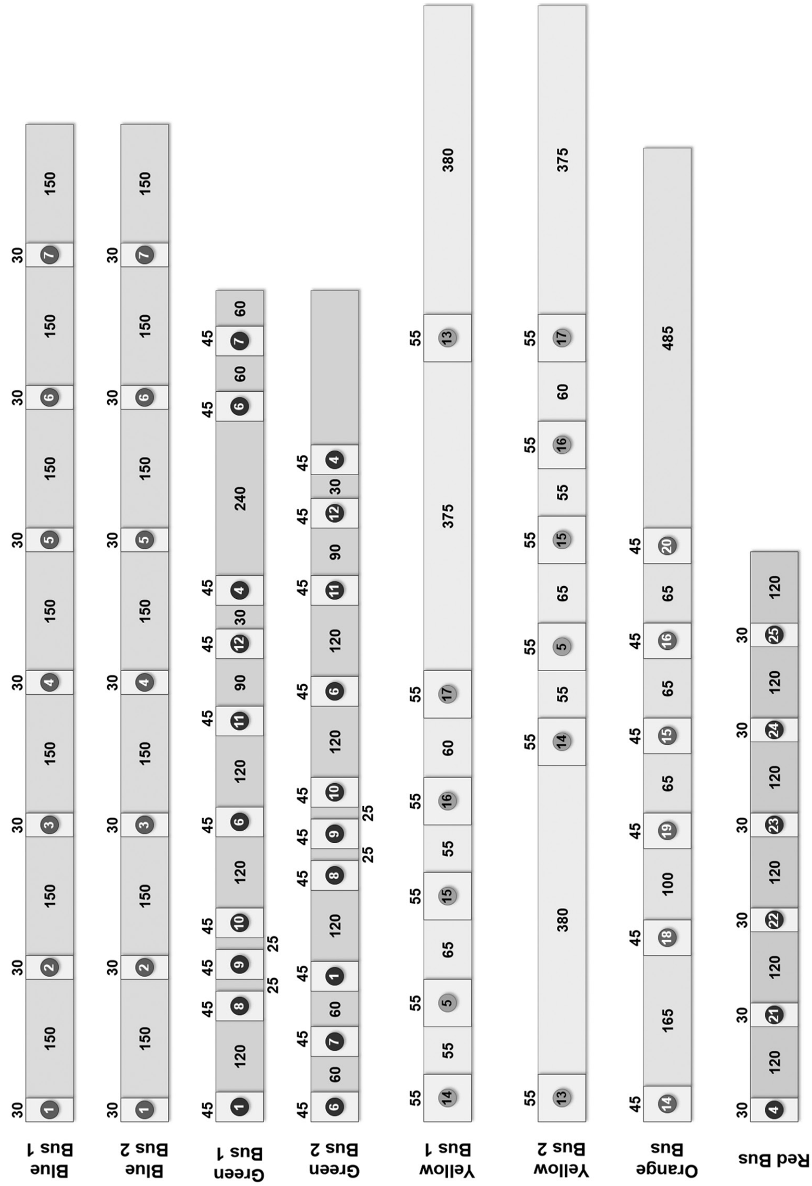

Figure 5.2 JagTran bus time schedule relative to stops on each bus route

Table 5.5 General traffic agent behaviors

Behavioral Attribute	*Assumption*		
Acceleration – m/s^2 (ft/s^2)	2.47 (8.10)		
Deceleration – m/s^2 (ft/s^2)	−3.27 (−10.73)		
Max deceleration – m/s^2 (ft/s^2)	−7.47 (−24.52)		
Headway – m (ft)	3 meters (9.843)		
Car Following	Krauss	Σ	0.4
		T	2.5 sec.

Observations were made at the same 10 traffic intersections as in the previous section. Turning movements at each intersection were obtained by taking 90-minute videos in peak morning and evening periods. These observations were used in calculating turning probabilities at intersections. These probabilities were then used as road network inputs for the simulation. Simulated traffic demand was dynamic with flowrates varying hourly.

5.3.1.2.2 Traffic behavior data

A class of traffic agents were created to provide noise within the bus route simulation to more closely resemble reality. Each general traffic agent was given behavior like that of a normal human. Assumptions for general traffic agent behavior such as kinematics, car following model, and headways were derived from [39, 55–60]. Table 5.5 provides assumptions for the input parameters used within the simulation for agents within the general traffic flow. In the simulation, general traffic demand agents were not given fueling behaviors and all agents were assumed to be cars.

In Table 5.5, the kinematics parameters such as acceleration and deceleration were assumed to be higher due to vehicle size, weight, and driver's propensity to drive less conservatively than bus drivers. This style of driving is expected to impact the sigma parameter and the headway. The value of Σ could not be found in literature for a car following model and was therefore assumed to be about 40% to account for inherent flaws and susceptibile errors of human drivers. Conversely, the value of T was obtained from the literature [52] providing typical reaction times for human drivers.

5.3.1.3 AB data

5.3.1.3.1 Specifications

In this chapter, ABs were used in place of HDBs. Data for existing JagTran buses were used in their specification. However, ABs data were minimally available. Most ABs have an electric charging configuration as opposed

Table 5.6 AB specifications and behavior assumed for each alternative fueling infrastructure

Specification Attribute	*Values*			
Fuel	Diesel/ Biodiesel	Propane/NG	Electric	Hydrogen (H_2)
Fuel Capacity	30 gal (1,111.1 kWh)	30 DGE (1,108.5 kWh)	144 kWh	9.78 kg H_2 + 28 kWh (354 kWh)
Seating Capacity	15+, varying with simulation			
Vehicle Chassis	Ford E450			
Length – m (ft)	7.28 (23.88)			
Width – m (ft)	2.44 (8.01)			
Height – m (ft)	2.88 (9.45)			
Vehicle front – m^2 (ft^2)	7.03 (75.7)			
Weight – kg (lb)	5,262 (11,578.7)	6124 (13,501.1)	6577 (14,500)	5561 (12,259.9)
Air Drag Coefficient	0.7	0.7	0.7	0.7
Roll Drag Coefficient	0.008	0.008	0.008	0.008
Radial Drag Coefficient	0.9	0.9	0.9	0.9
Propulsion Efficiency	0.33	0.33	0.73	0.44
Recuperation Efficiency	0	0	0.54	0.54

to other fueling options. These limitations led to the adoption of various assumptions regarding AB simulation (i.e., based on a Ford E450 specification manual) and behaviors. Table 5.6 provides assumed input values used for describing the behavior of the AB agents relative to each fueling infrastructure type.

Table 5.6 provides interpolated specifications of paratransit bus configuration with different powertrains. Specifications such as dimensions, drag coefficients, and seating capacity were kept constant across powertrains. However, due to the use of different powertrains, fuel capacities were varied due to the energy density of fuel medium. Propulsion and recuperation efficiency were also varied across powertrains due to inherent technological imperfections associated with powertrain conversion of fuel to vehicle movement and recovering power through regenerative braking. Vehicle weight across all powertrains were also varied due to certain powertrain architectures such as electric powertrains being heavier than other powertrains due mainly to battery elements.

In Table 5.6, there are some caveats to how some of the values were obtained. Firstly, fuel was measured as energy within the simulation environment. This required the conversion of real fuel-related attributes (gal of diesel, kg of H_2, liters, etc.) to energy equivalent units. Data in Table 5.6 specifies energy in typical units of measure for each fuel.

5.3.1.3.2 Behavior

Information about the behavior, performance, and architecture of ABs is sparse in the literature. To overcome this, assumptions about the performance behavior expected from the ABs were made based on literature studies [39, 49, 52]. Table 5.7 provides the assumptions used for AB-related behavior. The idea in Table 5.7 was to use values indicative of more precise and less imperfect habits seen in human driving behavior. This was accomplished by reducing acceleration from 1.9 m/s^2 to 0.9 m/s^2 and deceleration from –1.45 m/s^2 to –0.9 m/s^2 to increase ride quality for passengers [49]. Headways were decreased from 4 meters to 1 meter due to ABs possessing more precise and efficient driving strategies than their human-driven counterparts [39]. In the car following model, the Σ parameter was assumed to be 0 due to ABs having near perfect driving due to presence of sensors and fast computing resources for split second decision-making. Conversely, the T parameter was reduced from 2.5 sec to 1 sec because of AB's quicker reaction time than HDBs [52]. Lastly, the bus loading durations per passenger were reduced due to potential reductions in boarding time associated with augmented boarding protocols in using ABs. Additionally, refueling of ABs was only allowed if a minimum 40% of the fuel capacity was depleted and there were no passengers on the bus at time of the fuel capacity threshold being reached. This allowed for adequate comparison across the fueling and charging infrastructures.

5.3.1.4 Fueling infrastructure data

5.3.1.4.1 Rate of refueling

Safety and other factors influence safe rates for vehicle refueling. Table 5.8 shows the rates that were used to control the simulation.

The refueling rates in Table 5.8 were converted to watts per hour to conform to the required format in SUMO. Equation 5.1 shows the formula for conversion of the values in Table 5.8.

Table 5.7 AB agent behavior and their assumptions

Behavioral Attribute	*Assumption*		
Acceleration m/s^2 (ft/s^2)	0.9 (2.95)		
Deceleration m/s^2 (ft/s^2)	−0.9 (−2.95)		
Max deceleration m/s^2 (ft/s^2)	−1.0 (−3.28)		
Headway m (ft)	1 (3.28)		
Following Model	Krauss	Σ	0
		T	1 sec
Loading Duration (per Passenger)	1.5 sec		

Table 5.8 Refueling rates supporting simulated JagTran

	Fuel/Infrastructure Type					
	Diesel/ Biodiesel	*Propane/NG*	*Electric*	H_2	*BST/BSS*	*WPT/Inductive Charging*
Rate	3000 kW/h (13.50 gal/ min)	3000 kW/h (39.10 kg/ min)	180 kW/h	2890 kW/h (7.2 kg/min)	750 kW/h *(Figurative Value)*	200 kW/h

Table 5.9 Refueling durations for each infrastructure type

	Infrastructure Type					
	Diesel/Biodiesel	*Propane/NG*	*Electricity*	H_2	*BST/BSS*	*WPT/Inductive Charging*
Fueling Duration (min)	15– HDB; 10– AB	10	50	5	10	-

$$FR_{actual} = FR_{sim.}\left(t_{charge}\right)0.027 \cdot FT_{cf}$$

$$where\ FT_{cf} = \begin{cases} 1.111,\ hydrogen \\ 2.896,\ propane\,/\,natural\,gas \\ 1.0,\ diesel\,/\,biodiesel \end{cases} \qquad 5.1$$

FR_{sim} is the fuel dispensing simulated flow rate, FT_{actual} is the actual rate of fuel flow, t_{charge} is the duration of fueling, and FT_{cf} is the conversion factor for the fuel type. Using FT_{cf} ensures that the simulated rate is in appropriate units.

5.3.1.4.2 Duration of fueling

The durations vary based on different factors, including safety, that dictate a safe refueling rate. Simulated maximum refueling durations were assumed from elicitation and literature. In Table 5.9, the fueling infrastructures were modeled in accordance with their fueling durations, but the diesel/biodiesel fueling infrastructure was modeled for HDB and AB refueling cases.

Fueling duration in Table 5.9 were based on common fueling durations seen in existing literature and empirical data. In the diesel/biodiesel fueling durations, a difference between the HDB and AB fuel duration were due to assumption that HDBs may take extra time to fuel due to human-related causes, while ABs could be refueled with some automated fueling system with little to human-intervention. Fueling duration for the electric charging infrastructure was assumed based on a fast-charging configuration.

5.3.1.4.3 Simulation environment setup

Once all datasets were collected, they were implemented into SUMO. This process consisted of replicating the USA bus network (e.g., bus routes, stops, fleet configuration) in SUMO. Figure 5.3 shows the simulated campus in SUMO that was used to simulate JagTran bus fleet scenarios. The JagTran buses were not allowed to deviate from their bus routes unless they needed to be refueled at the fueling/charging station which was located on campus as seen in Figure 5.3.

5.3.2 Model validation

5.3.2.1 Variation analysis of ridership demand

The intent of the ridership demand analysis was to aggregate a month of hourly real JagTran ridership demand data to form threshold values. The real and the simulated ridership demand were compared to assure their quantities were similar. Figure 5.5 shows the comparison of ridership demand comparison for all JagTran buses. In Figure 5.5, the box plots are indicative of the actual ridership demand distribution, while the line plot represents ridership demand distribution generated from SUMO. Based on Figure 5.5, the model was valid in terms of ridership demand due to the simulated ridership distribution resembling the actual ridership distribution by mostly staying within the box plot's interquartile ranges.

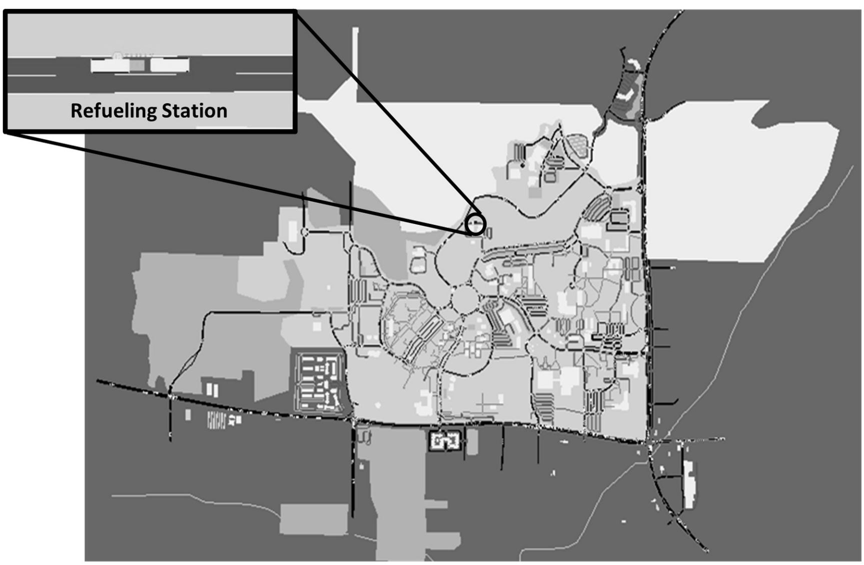

Figure 5.3 The road network layout used in the simulation cases (SCs)

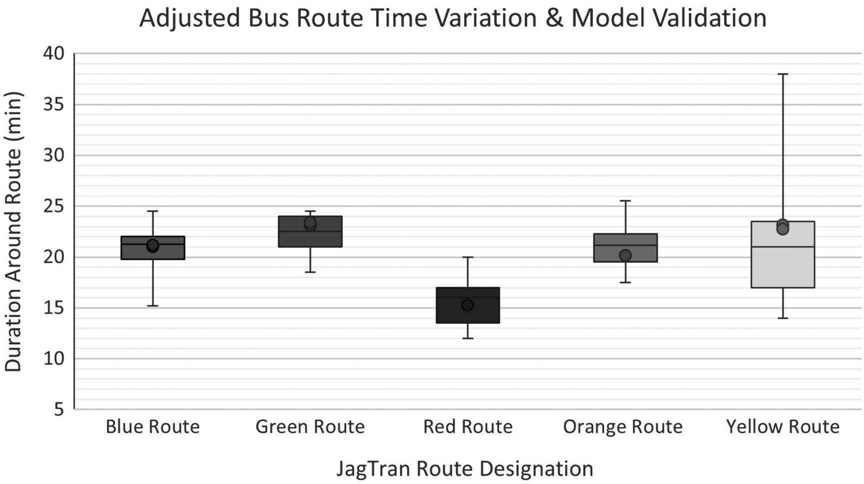

Figure 5.4 Model validation of real and simulated route times variation

5.3.2.2 Route variation analysis

The aim of using the route variation analysis approach was to evaluate the 18 random bus route loop times (i.e., 10 loop times for orange bus) from a large GIS dataset. From here the loop times were aggregated into a box plot to visualize variations in route times and to determine time ranges acceptable for each route (as seen in Figure 5.4). These box plots were used to act as indicators to determine if the simulated bus route loop times generated in SUMO were within an acceptable range relative to the actual bus route loop times. The dots in Figure 5.4 represent the simulated bus route times. Within Figure 5.4, it shows that simulated bus loop times within SUMO were within the interquartile range of the boxplots indicating their high similarity to the actual JagTran route times. Based on these findings, the simulation was valid in terms of route loop times.

5.4 EXPERIMENTATION

Following model validation, simulation experiments were conducted which consisted of performing five case studies (as seen in Table 5.10).

In Table 5.10, each SC is presented along with its intended goal for the SC and the treatment that informed the DoE. Each of the SCs in Table 5.10 are not isolated cases (i.e., except for SC5) but are linked SCs that form an interlinked process where output from one case feeds another. Within each of the SCs in Table 5.10 are simulation scenarios run 10 times each to support statistical analyses.

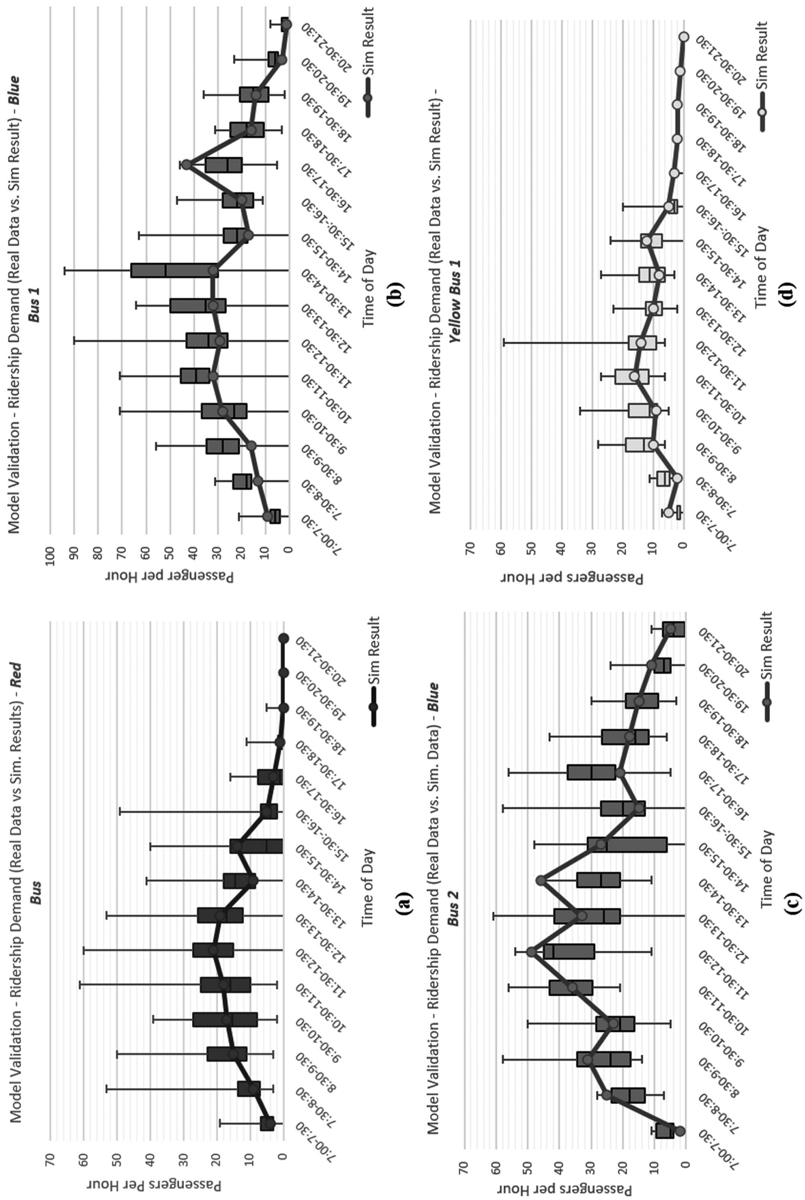

Figure 5.5 Model validation of ridership demand

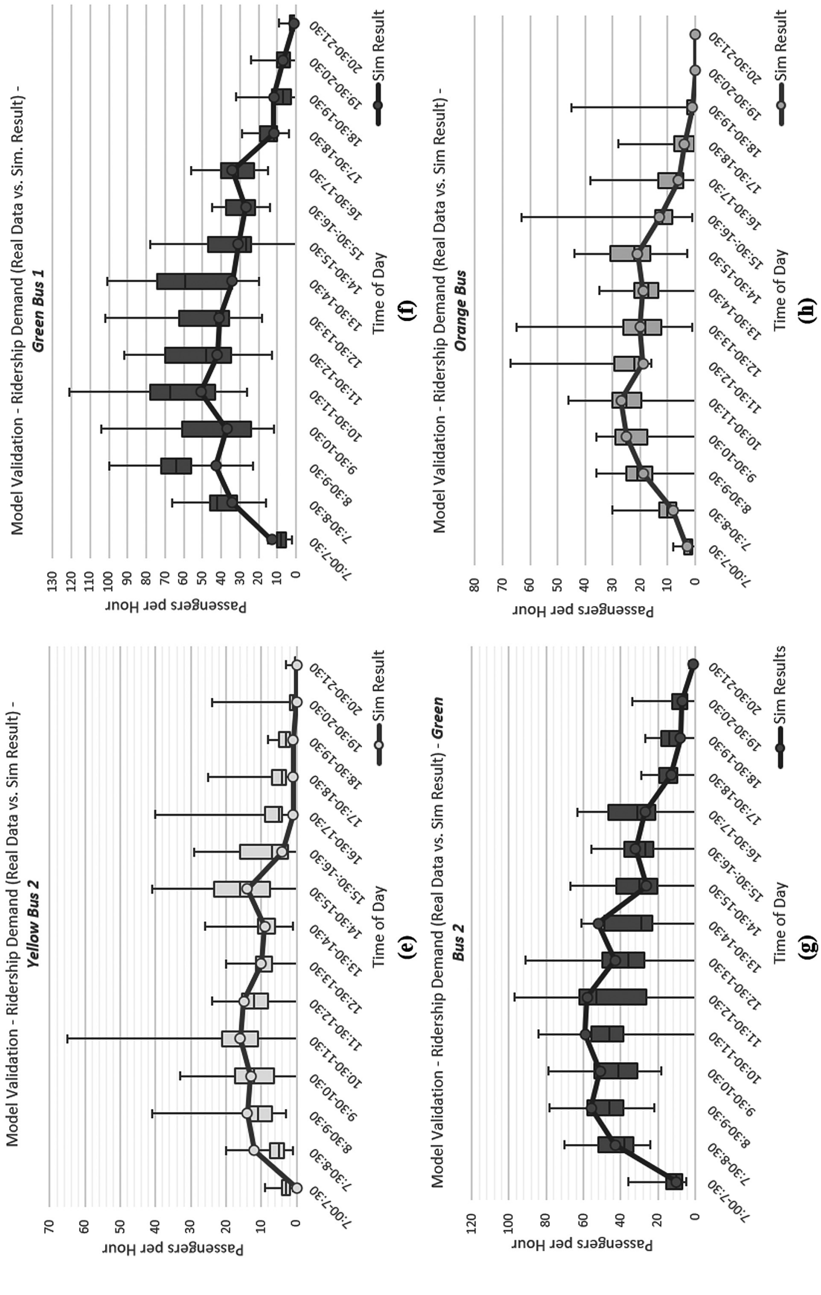

Figure 5.5 (Continued)

Table 5.10 Simulation cases and their respective descriptions or goal

Simulation Case (SC)	*Description/Goal*	*Treatment*
SC1 – Fueling Infrastructure Variation	Cases that vary fueling infrastructure integration in the JagTran bus fleet.	Different fueling infrastructure used across scenarios. Best fueling infrastructure used throughout SC2-SC4.
SC2 – Ridership Demand Variation	Cases concerned with the impact of ridership variation on the JagTran system's performance.	Ridership increased by 5% increments until base case wait times from SC1 is reached.
SC3 – Vehicle/Fleet Configuration Variation	Cases investigating the impact of vehicle/fleet capacity on the JagTran system's performance.	Capacity increased by 1 seat per bus until wait times begins to decline.
SC4 – Hybridized Fueling Infrastructure	Cases considering simultaneous use of more than one fueling infrastructure and buses with different autonomy levels in the JagTran system architecture.	Penetration rates of automated H_2 buses at 0, 25, 75, 100% of bus fleet.
SC 5 – Fueling Infrastructure Improvement	Cases dedicated to understanding the impact of using emerging fueling infrastructure technologies in the JagTran system.	BSS/BST implemented at on-site fueling site and IC/WPT installed at all bus stops.

5.5 RESULTS AND DISCUSSION

Data analysis used two metrics of interest: passenger wait time and fleet-level fuel cost. Passenger wait times allowed for the calculation of throughput, while fleet-level fuel cost/km was used as a measure of the quality of mobility provided. A secondary metric of interest that was examined was carbon dioxide (CO_2) emission factors which was used in deciding the best fueling infrastructure (in SC1). CO_2 emission data were taken from [65] and were not outputs of the SUMO but were calculated.

5.5.1 Fueling infrastructure simulation case results

In Figure 5.6a, results showed that in terms of passenger wait times, ABs-NG infrastructure performs the best at 5.65 $\pm$ 3.96 min. Considering fuel cost per kilometer, ABs integrated with a plug-in electric infrastructure performed the best at \$0.45 USD/km. However, considering both wait time and fleet-level fuel cost/km, the best fueling infrastructure was ABs-H_2 which had an average wait time of 5.73 $\pm$ 4.04 min and a fleet-level fuel cost of \$0.88 USD/km. Furthermore, in Figure 5.6b, it is shown that, when based on emission and fuel cost, the best fueling is the AB-electric

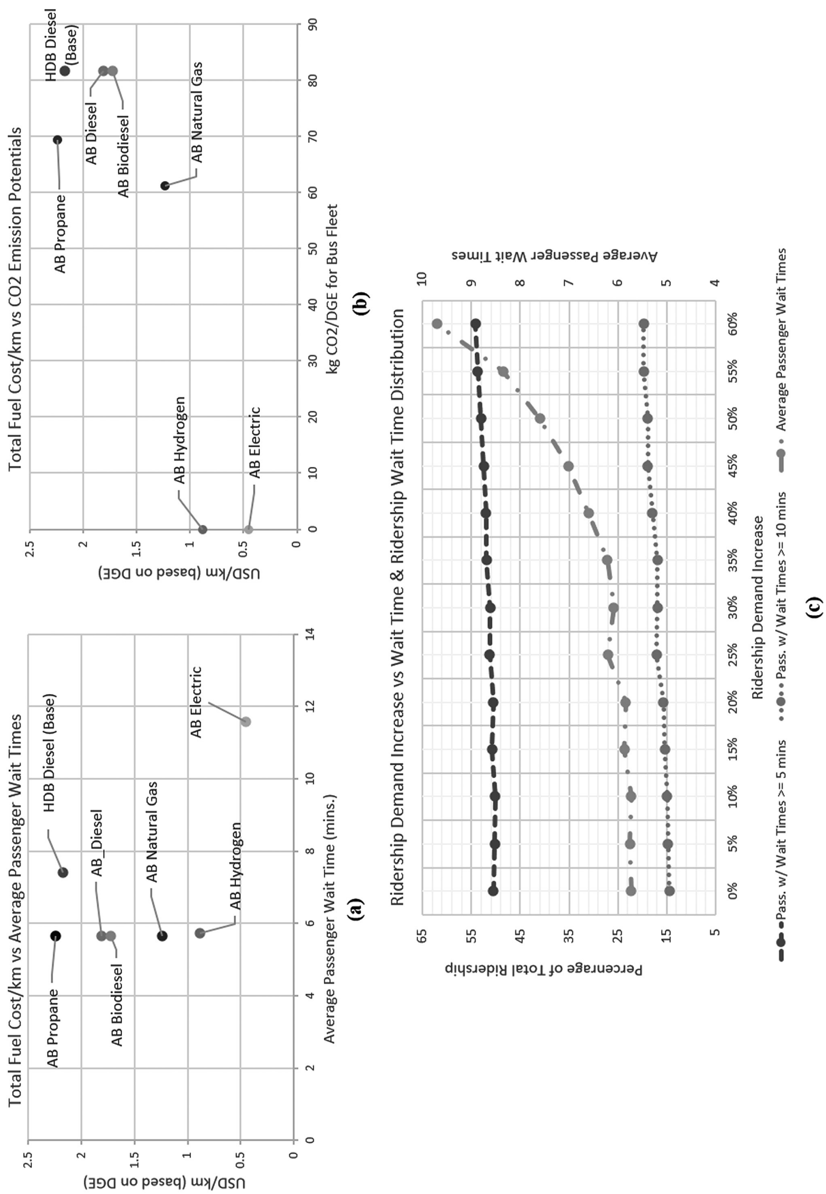

Figure 5.6 Fueling infrastructure variation and variation of passenger ridership impact on average wait time

infrastructure due to its zero emissions, but with the long fueling duration of electric infrastructure, the AB-H_2 infrastructure is better. Therefore, the best fueling infrastructure based on emissions, fuel cost, and average passenger wait time is the AB with H_2 fueling infrastructure.

5.5.2 Usage demand simulation case results

In SC2, ridership across scenarios was incrementally increased by 5% until the wait times resembled the base case wait time (7.40 ± 6.22 min). Figure 5.6c shows the impact of an increased ridership demand on passenger wait times and the distribution across the rider population. Results from Figure 5.6c revealed that as ridership demand increases, average wait times exponentially increase, and the wait time distributions linearly increase. Findings also showed that the AB-H_2 infrastructure system has the same average wait time as the base case when the demand has reached roughly a 49% increase. This means above 49%, the increased ridership may indicate the need for an additional bus.

5.5.3 Bus/Fleet configuration simulation case results

Findings from SC3 which consisted of varying vehicle capacity are shown in Figure 5.7.

Figure 5.7 shows that as seating capacity within the buses (or bus fleet) increased, average wait time and their distributions followed a U-shaped profile. At the bottom of the profile, average wait times were minimized for seating capacity ranging from 13–30 seats per bus (or 104–240 seats for the fleet). These findings were used to assess the impact of using a different bus configuration from what was used in SC1 and SC2 (a 15-seat capacity bus). Therefore, a 23-seat capacity bus akin to a mini-coach/microbus

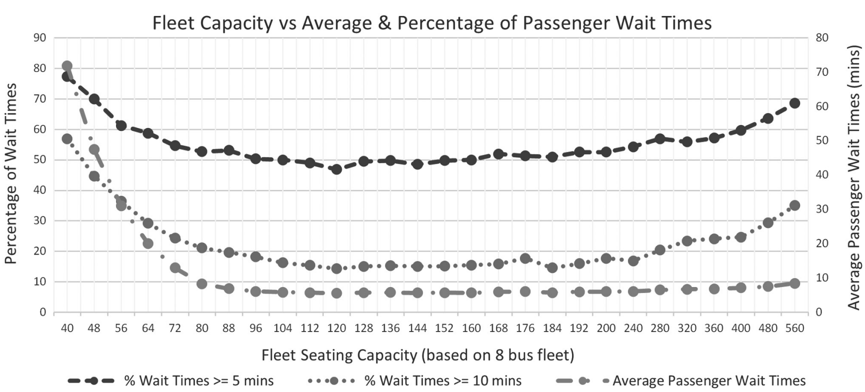

Figure 5.7 Influence of bus/fleet seating capacity variation on transit wait times

configuration was utilized. Assumptions for specification such as vehicle specifications were assumed using a Ford F550 specification manual and can be seen in Table 5.11. With a mini coach configuration being used as opposed to a paratransit bus, specifications such as engine power, fuel and seating capacity, dimensions, and vehicle weight were all increased.

Figure 5.8a shows the fuel cost per kilometer for each bus within the base case, AB paratransit, and AB mini-coach configurations. By adjusting the bus specifications within the simulation, using a mini/microbus configuration led to a mean wait time of about 6.04 ± 4.78 min. Relative to the base case, this amounted to a reduction of about 20.2%. However, utilizing a mini/microbus, which utilizes a large capacity did lead to a 46.3% increase in fuel cost when compared to the best performing fueling infrastructure. However, in respect to the base case, the utilization of a H_2 mini/microbuses saw a 42.2% reduction at the fleet-level.

5.5.4 Fleet and infrastructure hybridization simulation case results

Results from SC4, which are depicted in Figure 5.8b, revealed that as hybridization increased fleet-level fuel cost/km decreased along with average wait times. Across all scenarios, average wait times of 6.84 ± 5.58 min, 6.28 ± 4.96 min, and 5.96 ± 4.67 min were acquired; respectively. This translated to passenger wait times that gradually decreased as autonomy and fueling hybridization or mixing of the JagTran fleet increased. In observing Figure 5.8b, one can see that as the penetration rate increases a slightly nonlinear decrease in average wait time versus fuel cost is achieved.

Further results in Table 5.8c also showed that with increased incorporation of hybridization within the JagTran bus fleet, reductions in CO_2 emissions factors can be achieved. What is more, as the JagTran bus system

Table 5.11 Vehicle attributes for utilized for AB-H_2 mini coach bus configuration

Specification Attribute	*Assumed Values*
Bus Fuel/Powertrain Type	Hydrogen
Bus Propulsion	19.28 kg H_2 + 28 kWh (670,667 kWh)
Seats	23 seats
Engine Power (kW)	280
Vehicle Chassis	Ford F-550
Bus Length – m/(ft)	10.06/(33.01)
Bus Width – m/(ft)	2.44/(8.01)
Bus Height – m/(ft)	3.16/(10.37)
Bus Frontage Area – m^2/(ft^2)	7.71/(83.06)
Bus Mass – kg/(lbs)	9014/(19,782)

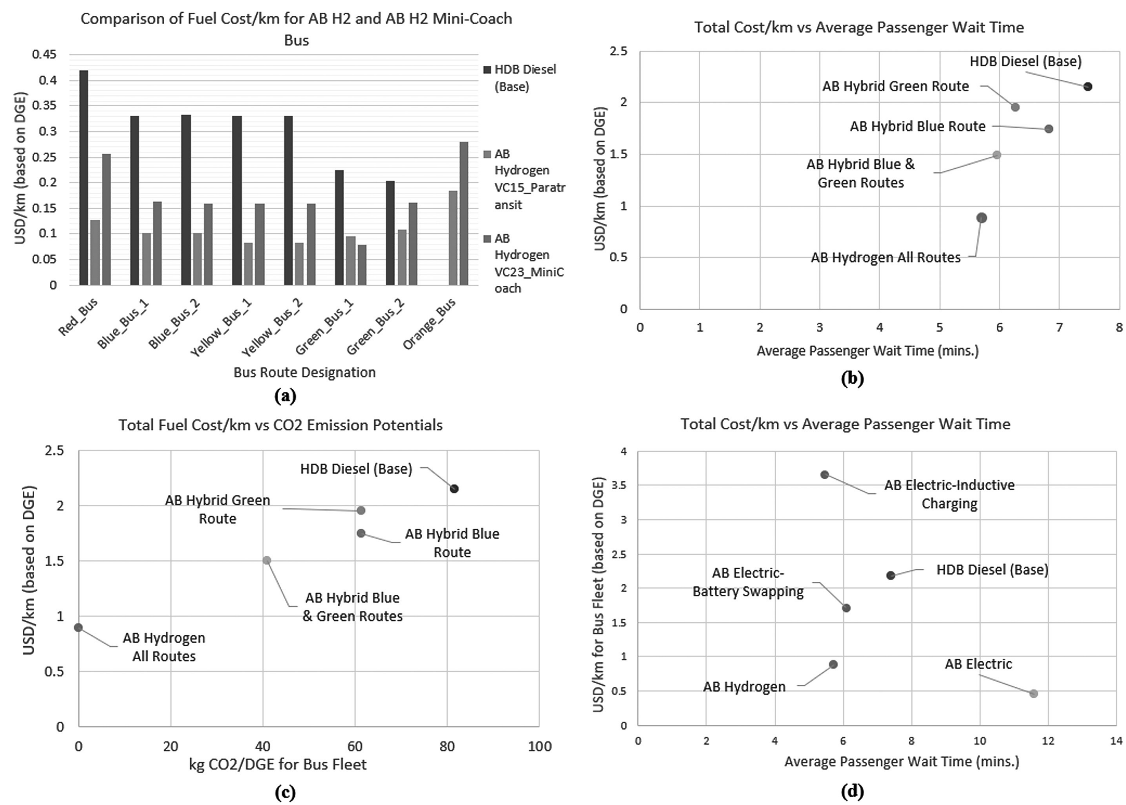

Figure 5.8 a) Comparison of fuel cost of base case relative to AB H_2 paratransit and mini-coach configurations, b) hybridized bus fleets bus fleet configurations, c) emerging fueling/charging infrastructures

continues to evolve, reductions in fleet fuel costs on the order of 9.76%, 20.6%, 35.8%, and 83% were obtained when placing H_2-powered ABs on the blue route, green route, both blue and green routes, and all bus routes; respectively. The same trend was observed for fleet-level CO_2 emissions factors where 28.6%, 66.7%, and 200% reductions were achieved by using ABs with H_2 on blue, green, both blue and green, and all bus routes; respectively

5.5.5 Emerging fueling infrastructure simulation case results

Obtaining the fleet fuel cost per kilometer for BSSs/BSTs consisted of two major assumptions regarding *electricity fuel cost* and the *service fee* associated swapping the battery of a given bus for recharging/refueling operations. Utilization of the BSS/BST system in the simulation was conceived or modeled to be a Battery as a Service (BaaS) business model platform where services were provided by a third-party company. If this is assumed, then a monthly service fee may be charged for using their proprietary technology including battery packs, automation services, maintenance services, etc. Further electricity costs may also be derived from powering other BSS components such as robotic service systems, this however is not the focus of this chapter. The BSS/BST fuel-related cost was determined by using Equations 5.2 and 5.3.

$$Fuel\,Cost_{BSS} = cost_{electric} + cost_{BSS\,Service} \qquad 5.2$$

$$where,\; cost_{BSS\,Service} = \frac{S_{fee} \cdot t_{op.}}{d_i} \qquad 5.3$$

where, $cost_{electric}$ represents the electricity costs for powering the BSS, s_{fee} indicates the monthly fee in hours for providing BSS services, $t_{op.}$ stands for the accumulated amount of time the BSS is operated, and d_i is the total distance driven during operations. In Equation 5.2, the $cost_{electric}$ was assumed to be equivalent to about \$0.14/kWh. For s_{fee}, NIO's BaaS plan [61] was used to assume monthly fee in Equation 5.3. Through some approximation from external sources [62, 63], the s_{fee} for using the BSS/BST was assumed to be about \$380/month (\$18.10/day). Therefore, s_{fee} in Equation 5.3 was equivalent to a monthly fee of about \$380/month (or \$18.10/day). For the WPT/IC integration, the only applicable cost was the $cost_{electric}$ which was \$0.14/kWh.

Figure 5.8d shows the results from integrating ABs with BSSs/BSTs and IC/WPT infrastructure relative to other JagTran fleet architectures. Results from Figure 5.8d revealed that when BST/BSS and WPT/IC are used in concert with ABs, mean wait times of about 6.08 $\pm$ 4.53 min and 5.47 $\pm$

3.76 min were obtained; respectively. Relative to the base case, these wait times from using BSSs/BSTs and WPT/IC translated to a 19.6% and 30% reduction in wait times; respectively. Fleet fuel costs per unit km saw 23.7% savings relative to when ABs are used with diesel fueling infrastructure (i.e., base case). However, using WPT/IC culminated in a 72.6% increase in fleet fuel costs per unit km. This was primarily caused by the WPT/IC pads being placed at every bus stop, increasing fuel costs. Additionally, when BSS/BST and WPT/IC were used, the mean passenger wait times were reduced by about 62.3% and 71.7% compared to when a traditional plug-in charging infrastructure was utilized.

5.5.6 Hypothesis testing

5.5.6.1 Hypothesis 1

The first hypothesis was addressed through the results seen in SC1 in the second scenario. The Mann–Whitney–Wilcoxon (MWW) test was applied to compare these wait times statistically for all three hypothesis tests. Table 5.12 shows the outputs from the hypothesis test. In Table 5.12, μ_{base} indicates the mean passenger wait time or throughput for the base case and $\mu_{ab\_d\_biod}$ represents the mean throughput when ABs are utilized with diesel fueling stations. Hypothesis testing showed there was statistical significance in the average wait time between the base case and when ABs are used in tandem with diesel fueling stations.

5.5.6.2 Hypothesis 2

The results obtained through SC1 were used for addressing hypothesis testing for this research conjecture. Table 5.12 provides the composition of the MWW test which aids in hypothesis testing. In Table 5.12, μ_{ab_h2} represents the mean passenger wait time for ABs-H_2 refueling station. Hypothesis testing showed statistical significance in average wait time between the base case and using ABs-H_2 fueling infrastructure. ABs-H_2 can provide increased reliability over the existing JagTran architecture.

Table 5.12 Hypothesis 1 and 2 testing results from MWW test

	Hypothesis 1	*Hypothesis 2*
Null	$\mu_{base} < \mu_{ab\_d\_biod}$	$\mu_{base} < \mu_{ab\_h2}$
Alt.	$\mu_{base} \geq \mu_{ab\_d\_biod}$	$\mu_{base} \geq \mu_{ab\_h2}$
z-scores	−24.054	−22.3784
p-value	< 0.00001	< 0.00001
Alpha – α	0.05	0.05
Result	**p < 0.05, Reject Null**	**p < 0.05, Reject Null**

5.5.6.3 Hypothesis 3

The third hypothesis was addressed through results created from SC3 and SC4. This hypothesis was disseminated into two parts: the *first* part being addressed through the results from SC3 of this study, and the *second* being addressed through SC4 results. The MWW test was applied to assess statistical significance between the wait times seen in the base case, SC3, and SC4.

Statistically comparing the wait time results of SC3 to SC1 through the MWW test, Table 5.13 shows hypothesis test results of part one of hypothesis 3. In Table 5.13, $\mu_{ab\_h2\_MiniC}$ is the mean passenger wait time for the AB-H_2 mini-coach configuration. Findings from the hypothesis testing showed using a mini-coach bus configuration significantly decreases wait time relative to that seen in the base case. The second half of hypothesis 3 found statistical significance when different AB configurations and fleet hybridization were used. In Table 5.13, $\mu_{ab\_Hyb\_Bl}$ is the mean wait time when AB-H_2 is used on the blue route, $\mu_{ab\_Hyb\_Gr}$ is the mean wait time when AB-H_2 are used on the green route, and $\mu_{ab\_Hyb\_Bl\_Gr}$ is the mean wait time when AB-H_2 are used on the blue and green routes.

5.5.7 Discussion

In all, changing the bus autonomy and fueling infrastructure significantly reduced wait times and fuel cost per kilometer in comparison to the base case. However, an average wait time of less than 5 min was not achieved by any of the fueling or charging infrastructures from SC1. One means of achieving this mark could be to use a bus in the occurrence of long fueling/charging times or unexpected downtimes. However, large capital costs may be accrued due to the need for additional buses within the fleet.

In SC5, hybridization of the bus fleet in fuel and autonomy permitted market improvements in transportation performance and quality compared to the base case. This finding agrees with the concept of system hybridization

Table 5.13 Hypothesis 3 testing results from MWW test

	Part 1	*Part 2*		
Null	$\mu_{base} < \mu_{ab\_h2\_MiniC}$	$\mu_{base} < \mu_{ab\_Hybrid\_Bl}$	$\mu_{base} < \mu_{ab\_Hyb\_Gr}$	$\mu_{base} < \mu_{ab\_Hyb\_Bl\_Gr}$
Alt.	$\mu_{base} \geq \mu_{ab\_h2\_MiniC}$	$\mu_{base} \geq \mu_{ab\_Hyb\_Bl}$	$\mu_{base} \geq \mu_{ab\_Hyb\_Gr}$	$\mu_{base} \geq \mu_{ab\_Hyb\_Bl\_Gr}$
z-scores	−19.6965	−7.4446	−15.9769	−20.9431
p-value	< 0.00001	< 0.00001	< 0.00001	< 0.00001
Alpha – α	0.05	0.05	0.05	0.05
Result	**p < 0.05, Reject Null**	**p < 0.05, Reject Null**	**p < 0.05, Reject Null**	**p < 0.05, Reject Null**

which was found to be beneficial in [64]. Results from SC5 showed that further reductions in transport quality and performance could be achievable. For instance, fleet hybridization could be expanded to bus routes outside of the blue and green routes (i.e., to include the yellow, orange, and red routes) by having these routes use electric ABs or HDBs with WPT/IC. If WPT/IC is strategically placed at bus stops, opportunistic charging could further reduce refueling downtimes, fueling costs, and maximizing charge time. In SC5, from a wait time perspective, AB-BSS/BST integration were comparable with H_2-powered ABs. With BSSs/BSTs and WPT/IC, fleet augment for electric ABs won't be needed due to lower refueling times. BSSs/BSTs do have three major disadvantages. The first is battery management cost that is derived from procurement in support of battery swapping services. Next to this disadvantage is the sustainment intricacies behind these stations as part of a transit system. BSS/BSTs are composed of components such as power and software-intensive subsystems that bolster station-level automation which could incur significant maintenance costs over time. Thirdly, are the logistical and infrastructural impacts of using BSSs/BSTs. Batteries are the heaviest component on a bus. Rutting of roadways could grow due to heavier electric bus loads causing increased infrastructure maintenance costs [65].

Using WPT/IC showed both promising and concerning results. From a positive standpoint, it was determined placing WPT/IC platforms at each JagTran stop provided infinite driving range for buses, which made the JagTran bus system function more like a 'wireless trolley system'. In terms of negative impact, it was determined that with the integration of WPT/IC at each individual JagTran stop, this increased bus fleet charging/fueling costs/km. To overcome this, WPT/IC infrastructure could be properly designed based on social and sustainability needs.

5.6 CONCLUSION

ACs have been given an extensive amount of focus throughout literature in previous years. However, this level of attention has been lacking for ABs. Also, with previous literature tending to assume the powertrain of AVs or ABs as BEVs, as the production and use of BEVs increase over time, questions regarding scaling around BEVs will need to be addressed. This chapter begins to address this issue by exploring the transportation architecture potentiality of automated transit systems and their incorporation with current and emerging fueling/charging technologies.

In this chapter, the traffic simulation tool known as SUMO was leveraged to evaluate the systemic effect of integrating ABs and alternative fueling/charging infrastructure technologies could have on passenger wait times and fleet-level fuel costs. The USA campus was used as the operational environment in this simulation-based approach. The experimentation in this chapter consisted of five SCs. Results from all SCs showed that

when alternative fueling infrastructures are integrated with ABs, significant reductions in throughput, fuel costs, and fleet-wide emissions are significantly reduced relative to the base case. The exception to this finding was the electric plug-in charging system which exhibited long average wait times due to long refueling times. These long wait times could be combated by increasing the size of the bus fleet; however, this could incur significant capital costs. On the other hand, the need for enlarging the bus fleet in the case of H2-powered ABs would not be required. Additionally, findings from both hybridizing the bus fleet and leveraging emerging charging technologies showed significant promise by outperforming the base case in wait times, fleet fuel cost/km, and CO_2 emissions factors. This provided evidence that in future research, more care and attention need to be made in architecting existing and future automated transit systems.

5.7 FUTURE WORK

Simulation findings from this study were performed in a university campus environment. However, future work will focus on the simulation of transportation architectures in other CSEs (e.g., airports and military installations). Additionally, it is intended to integrate this M&S approach into a novel system framework known as the Biologically Inspired Organization for Transportation Architectures (BIOTA) [66] which leverages MBSE (as a technology repository) and a genetic algorithm (a co-design partner) to provide a more intelligent exploration and search of transportation architecture possibilities.

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Chapter 6

Enhanced deep learning networks for advanced intrusion detection and prevention systems

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6.1 INTRODUCTION

Considering all of the global cyber-attacks on government and commercial domains, the IDS in the network has grown quickly in both business and academics [1]. Furthermore, cybercrime's yearly cost is significantly increasing [2]. The most harmful cybercrimes are primarily caused by hostile insiders, internet-based harmful incidents, and denial-of-service (DoS) attacks [3, 4]. Businesses that used network intrusion detection systems, firewalls, and antivirus software did so efficiently [5]. One of the main priorities is utilizing the system for intrusion detection (IDS) to quickly identify the attack's weakness in order to avoid cyber-attacks [6]. Network intrusion detection system (IDS) detection of malicious activities, including worms and viruses, and decentralized denial-of-service (DDoS) attacks, is another goal [7]. Techniques for identifying anomalies can be applied to analyze user actions, such as examining programmers that are run on a regular basis and gaining access to information that is not available to regular users [8]. Furthermore, the way the gadget is used greatly affects intrusion detection. When there is any unusual behavior or trending in the connection, it notifies you and keeps an eye on the security status of the smart devices. The non-invasive activity versus the intrusive ones is the underlying assumption of the peculiar system. These numerous servers serve the goal of providing security for users of various multiple protocols [9]. Even yet, it could be challenging to forecast the intrusion features utilizing the regularly connected sensors in the IDS framework because every user is different.

In order to predict the current intrusion features in the underlying network environment, computational models were incorporated into the forecasting function. To get better prediction results, these neural approaches are also applied in combination with other optimization principles and mathematical formulas. Additionally, several authenticating techniques were used to process the prevention function. A using machine-learning

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(ML) [10] concept for prediction has the drawback of being resource-intensive and time-consuming to analyses, especially for large datasets or network applications. Additionally, by putting the preventative mechanism in place for the anticipated dangers, the security mechanism has been satisfied [11]. As a result, a number of techniques are employed to process the prevention mechanism, such as the blocking of unwanted traits from the network system, the encryption model, and the authorization model [12]. Identifying fresh attacks is the main advantage of outlier identification. Among its drawbacks is the need for noise training, which makes it challenging to track naturally occurring variations in the distributions [13]. While intrusive behavior that seems normal can lead to missed observations, alterations can also cause false alarms. With anomaly-based algorithms, identifying and categorizing risks is difficult [14]. It requires continuous self-updating to function well because it cannot identify or report whole new assaults [15]. This requires additional time. Accuracy, rapidity, and dependability of attack prediction are critical success factors for intrusion detection systems [16]. Furthermore, neural and optimization functions frequently power IDS.

IDS are in high demand in digital applications, making them a popular topic in the domains of deep learning (DL) and algorithmic learning (ML) [17]. Prediction and prevention have been accomplished thanks to the DL's application. The DL's extensive hyper-parameters are what made it possible to achieve the greatest results. The best result has been made feasible by the extensive hyper-parameters that are available in the DL. The increasing daily growth of network facilities and network usage poses a challenge to network security for conventional security solutions. As a result, numerous researchers have been drawn to the network's IDS to present novel concepts in data security. When it comes to forecasting a harmful occurrence in network applications, the DL models have produced the best results [18].Here, the two main goals are highlighted, one is to detect the malicious factors from network system, and the other one is to enhance the classification and extract features from the collected dataset.

6.1.1 Background and problem statement

For network operations to protect data from outside sources, intrusion detection systems are the most important instrument. Here, NetFlow-based features created by Mohanad Sarhan [19] have been used to control the IDS system. Here, the tree topologies served as the basis for training the assault features. Following the execution of the attack prediction function, the errors are eliminated by the filtering procedure. Ultimately, the parameters undergo validation and comparison with alternative methodologies. Still, the forecasting process has taken longer than expected.

An auto encoder artificial neural model has been described by Giuseppina Andresini [20] to predict the current invasion into the neural network

system. Additionally, using benchmark datasets, the proposed model's competent score is verified. Network traffic is the primary attack activity that is anticipated from the benchmark dataset. Thus, the autoencoder model has been used to create a duplicate communication channel in order to reduce network traffic. The accuracy of the assault prediction has now peaked. Nevertheless, its error rate is quite high.

Lianbing Deng [21] applied machine learning to the wireless network architecture to forecast invasions. It is difficult to predict malicious occurrences in a mobile environment because of the regular network. Because users' locations within the network system have occasionally changed, transfer learning has therefore been used in stages to develop the attack detection model. Its design is intricate, nevertheless.

Security performance was chosen because of the IoT devices' size, power, and cost. In order to identify an efficient preventive mechanism, Mishra [22] have created a number of preventative methods for the IoT environment. Additionally, the pros and downsides of this intrusion prevention model review are used. Also, DDoS intrusion was used to test the prevention models. The best results for predicting malicious features have been obtained by deep networks.

Lopez-Martin [23] developed the framework for positive reinforcement training in the network architecture to detect and stop intrusion behavior. Furthermore, the planned scheme's functionality is confirmed using the AWID database. The experiment improved the pre-processing algorithm's error reduction result and yielded the highest possible harmful features forecast precision score. To complete the process, though, more resources are required.

Kim [24–25] designed the IDS architecture for web-based applications since it is the most crucial architecture for the modern network environment. Here, the convolution neural model's guiding principles have been used to the processing of the IDS. Additionally, information of spatial features has been introduced for precise detection. The outcomes in the spatial graphical model were obtained during the IDS execution procedure. As such, the strategy's implementation has taken longer and required more resources.

The most important duty for preserving the communication channel's privacy range is intrusion detection in the network application. IDS were therefore introduced and the growth of dangerous technology and hacking has been comparable to that of security applications. As a result, identifying the current harmful event is a difficult task. Some attacks were designed to mimic the behavior of normal users in order to keep an eye on how network communication functions. After gaining any credentials or private information, it has been rendered inoperable by causing transportation or incident problems. Furthermore, the entire process has collapsed if a collision has happened in the communication route. These problems have spurred this study on intrusion detection systems for network applications.

6.1.1.1 Key contribution

The following best describes this scientific endeavor's primary contribution: The CICIDS 2018 and NSLKDD were gathered from the typical site prior to receiving system instructions. As a result, a special KbDBIF with the necessary parameters to predict the fraudulent conduct was created. In order to find the malicious occurrences, the detrimental components in the chimp optimization's fitness function were also addressed. The best outcomes for hyper-parameter tuning in this instance came from including the krill herd fitness. Lastly, the robustness of the suggested model was assessed using the following metrics: execution time, f-measure, accuracy, recall, precision, and error rate. Another important addition to the suggested model is this: standard site data was initially used to train the system using cooperative network application data. This has led to the introduction of a unique BENM with suitable preventative system properties. Furthermore, the pre-processing stage removes mistakes prior to bringing the data into the classification stage, when features are obtained and malicious events are detected but ignored.

6.2 RESEARCH METHODOLOGY

6.2.1 Proposed KbDBIF layer design

For intrusion detection systems (IDS) in network applications, a novel deep belief intrusion forecasting (KbDBIF) architecture based on Krill herd was developed. Before the error-filtered data is added to the categorization process, the pre-processing module has already filtered the current noise. As a result, traits have been taken out and assaults have been located. Ultimately, metrics for performance were assessed and attack categories have been categorized. Figure 6.1 provides an architecture description.

The input layer of the KbDBIF handled the data import routines, whereas the hidden layer handled the noise filtering model. To make feature evaluation and categorization easier, the data that is free of errors is then added to the classification module. It has been helpful to include krill fitness through in classification phase in order to further attain the best classification outputs. The suggested model is assessed with the help of the CICIDS and NSL-KDD dataset. When examining the resilience of the system that was developed, these two datasets were taken into account because of their unique qualities.

Pre-processing phase: To achieve the intended outcomes and stability range, this stage is critical for all machine learning activities. Furthermore, cutting down on execution time is the primary goal of this filtering stage, which lowers computational complexity. Development and evaluation become challenging processes because to noise in the dataset. As such, the process has taken longer to finish. Eq. 6.1 describes the setup of the dataset and it denotes every piece of information found in the database.

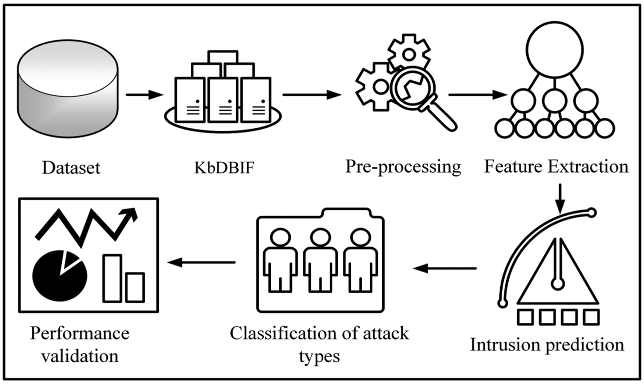

Figure 6.1 Proposed architecture of KbDBIF

$$X(S) = f(s_1, s_2, s_3, s_4 ....n) \tag{6.1}$$

$$N(i,f) = \frac{1}{2} x_f \left\| \ (n) - i \right\|^2 \tag{6.2}$$

The pre-processing is carried out in Eq. 6.2, where *S* represents the taken database, *i* and *f* represent noise features and normal featured factors. The taken dataset undergoes training and is denoted as *n*.

Feature extraction: Only the significant features remain in the dataset after the feature extraction process. There are both harmful and non-malicious components in the significant features. Using a classification function, the harmful and normal features are categorized. And finally, the feature extraction is carried out in Eq. 6.3.

$$Fr = \sum_{i=1}^{n} \alpha i [N(f) - x] = Xf \tag{6.3}$$

Here, F_r denoted the feature extracted factor and α represents the feature neglecting factor. And later, the meaningful features are stable and unwanted features were neglected.

Classification layer: The harmful and normal traits need to be identified after the significant features have been extracted. As a result, the best krill selection functions have served as the foundation for this specification procedure.

$$C(X_f) = \begin{cases} if\ (X_f = 0) & Benign \\ if\ (X_f \neq 0) & malicious \end{cases} \tag{6.4}$$

It is recognized as a regular user if the recorded features are in zero since the flexible ML for both 0 and 1. If the attributes are found to be 1, then it is malevolent occurrences. In the initial stage, the harmful and normal properties were distinguished by comparing the test data with the memory layer's stored data. Labels were applied after the testing phase, which involved comparing the test data to the recorded data. First, the KbDBIF memory layer was used to hold the benign and dangerous features. The assault data corresponding to the NSL KDD data were organized according to a predetermined scheme: normal files were placed in the normal class, DoS data in the DoS group, probe files in the test class, R2L data in the R2L class, and U2R data in the U2R class. Tested files are considered investigate when they are in the investigation class while being tested. However, if the files are in the ordinary class, they are classified as normal Figure 6.2 shows the working diagram of the proposed model and provides the functional architecture of KbDBIF. After initializing and training the data set, the relevant features are extracted using the Krill fitness function, and the data is then passed to the classification layer for CICIDS classification, where it is categorized as either normal or malicious. This process is done using KbDBIF to preprocess the data and filter out unwanted particles. Classification of KbDBIF is utilized for intrusion specification types such as Denial of Service, probing, Resource to Locator, and User to Resource after applying the CICIDS classification in the classification layer.

6.2.2 Proposed BENM model for network applications

To anticipate and disregard the attacks found in the datasets, a unique Buffalo-based Elman Neural Model (BENM) was created in addition to the login technique. Prior to the feature gathering and protection function being executed, any undesired noise is eliminated using the pre-processing method. In order to prevent the up-communing assault, the login technique has also been enabled. Therefore, the secret numbers in the user and necessary file details are part of the login technique. After that, the preventive parameters were verified and contrasted with those of other models.

Pre-processing phase: The Elman neural network and the buffalo optimization method make up the two components of the suggested BENM model. For the network detection method can start, the dataset need to be initialized. The attack on the dataset starts using the ABO technique in the same manner as Buffalo's. Pre-processing occurs after the data set has been trained and initialized. Pre-processing is mostly used to eliminate noisy features from the initial data. The process of eliminating noise characteristics in the input dataset leads to accurate intrusion detection. Additionally, there is a reduction in computing complexity and time.

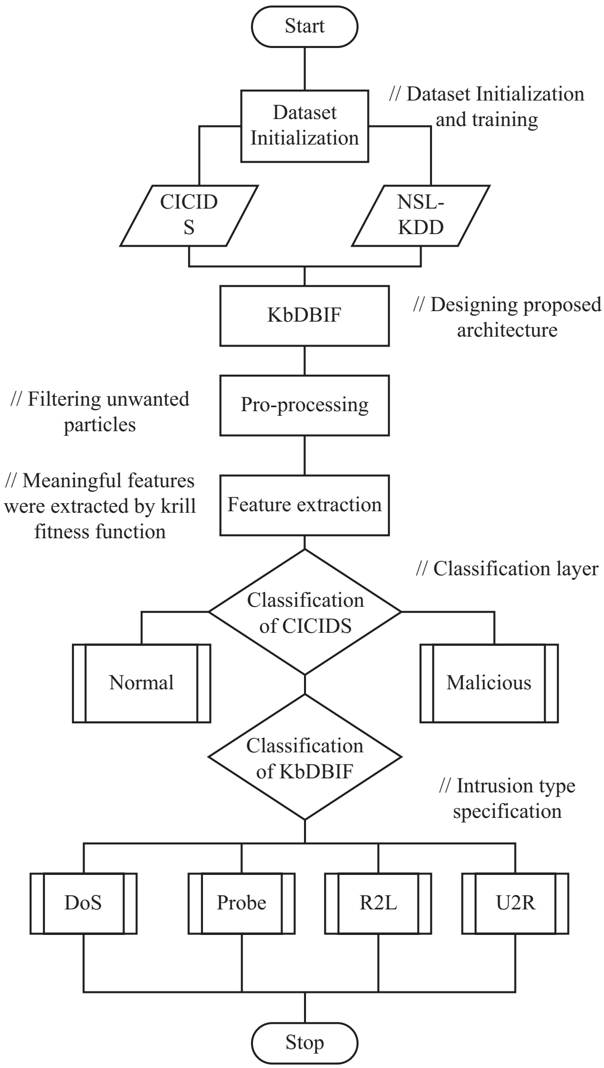

Figure 6.2 Working frame of KbDBIF

$$X[f_i(U,V)] = \sum_{i=1}^{N} f_i(U-V) \tag{6.5}$$

The pre-processing is carried out in Eq. 6.5. The taken database is represented as N, and i and f represent noise features and normal featured factors. The taken dataset undergoes training and is denoted as n.

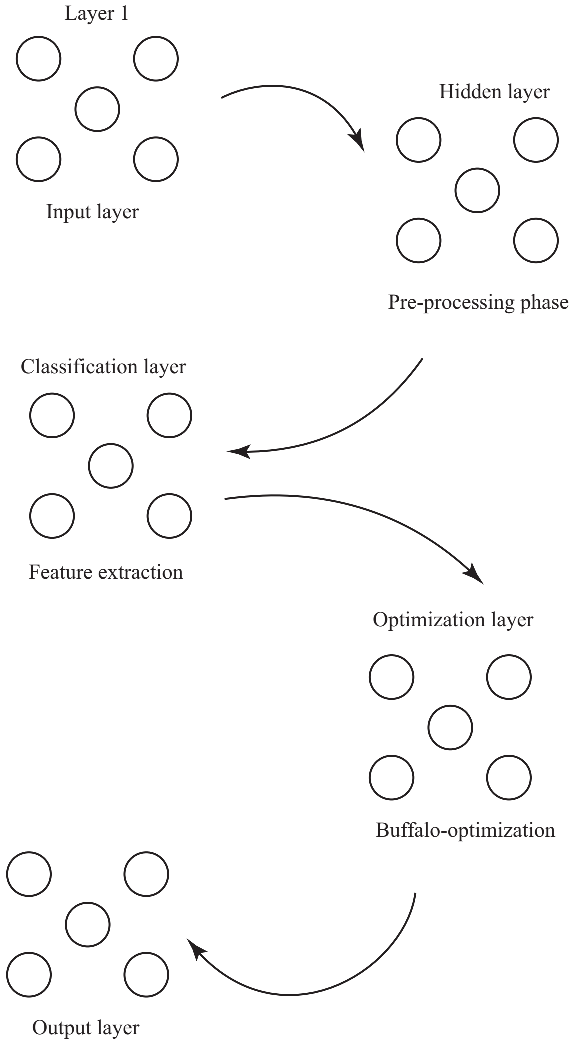

Figure 6.3 Proposed architecture of BENM

Feature extraction: Meaningful features are extracted from the dataset while meaningless features are ignored during the feature extraction process. Network intrusion detection is not too difficult after the unnecessary features are eliminated from the dataset. Before extracting useful and nonsensical features, the current qualities in the dataset need to be tracked.

$$G = \sum_{k=1}^{m} \alpha f[E(v) - z] = f_k \tag{6.6}$$

α for feature tracking indicates that fewer features are overlooked throughout the feature tracking procedure. Thus, the G used in the feature extraction procedure is specified and the useless feature is displayed.

Classification layer: Following this process of feature extraction, the dataset contains just the significant features. There are both harmful and non-malicious components in the significant features. A classification function is utilized to separate the harmful features from the normal features.

$$G(f_k) = \begin{cases} if(f_k = 0) & ; \quad benign \\ f(f_k = 1) & ; \quad malicious \end{cases} \tag{6.7}$$

The two states "0" and "1" represent the conditions for classification. The extracted characteristics are not malicious if they are in the "0" state. Alternatively, the characteristics are harmful if they are extracted and put to state "1." The dataset's classified characteristics need to be disregarded if they are attack features. An ongoing network monitoring technique is provided by a login approach after ignoring malicious features. The login technique takes into account two imperative constraints: "username" and "password." "Logged in" is displayed on the screen if the user provides the right "password" and "username." The "0" and "1" states correspond to the login criteria in this case. Once the authentication criteria are in the "0" state, the system indicates that the user is "logged in" and that the words "password" and "username" entered are correct.The model was created using the respective CICIDS and NSL-KDD datasets. These datasets have been pre-processed and trained in order to detect both benign and detrimental features. The dataset's harmful characteristics are eliminated following feature extraction. Additionally, a login approach is used to provide the network with ongoing monitoring. Figure 6.4 describes the working frame of designed model.

6.3 RESULTS AND COMPARISON

Preventing detrimental occurrences, or network attacks, is the primary goal of the architecture of the BENM model. Furthermore, a login mechanism is integrated to offer ongoing monitoring. Also, the KbDBIF is designed to predict the malicious features from the network. The datasets taken into consideration to validate the created model are CICIDS and NSLKDD. The table 6.1 contains particular mentions of the execution parameters. The intended model is implemented on the Windows 10 platform in a python environment. The reliability and accuracy range of the suggested model in predicting hazardous events was verified in this work by examining dual datasets like CICIDS and NSLKDD.

Accuracy: The metric's accuracy has been verified in order to calculate the detection rate of harmful features. Furthermore, accuracy has been assessed using the accurate prediction derived from the complete characteristics.

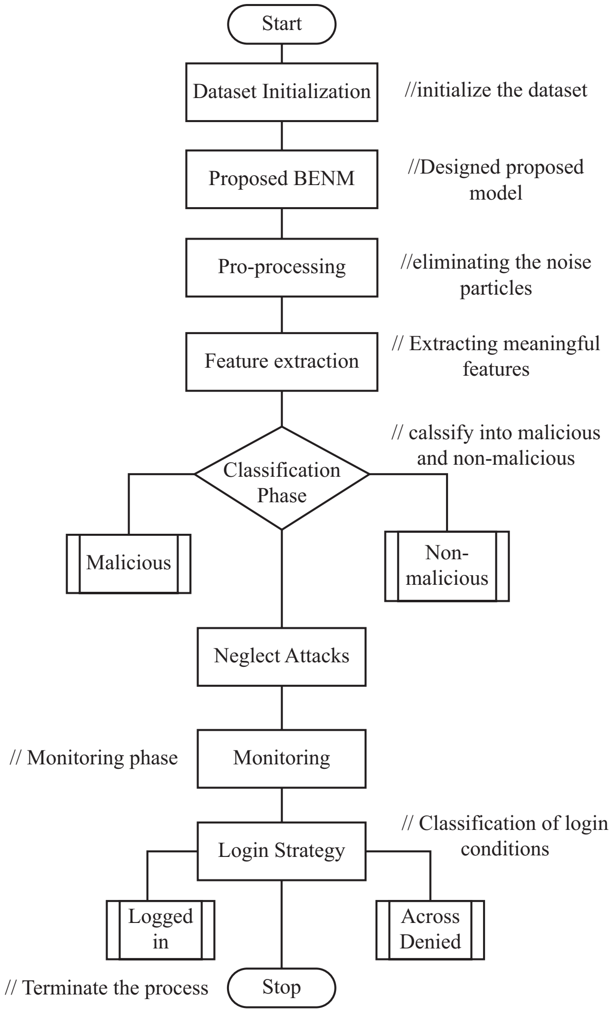

Figure 6.4 Working frame of BENM

$$Accuracy = \frac{R_p + R_n}{R_p + R_n + C_p + C_n} \tag{6.8}$$

where R_p represented the true positive and R_n denotes the true negative, C_p denoted the false positive and C_n denotes the false negative. The performance of the accuracy has been measured.

Precision: In the intrusion detection model, precision is the likelihood of achieving a positive score. Equation 6.8 represents the model's accuracy.

Table 6.1 Description of the parameters

Parameter configuration	
Application	Network
Version	3.8
Programming Platform	Python
Datasets	CICIDS and NSL-KDD
Operating System	Windows 10

$$\Pr ecision = \frac{R_p}{R_p + R_p} \tag{6.9}$$

True and false positives are used to measure the model's precision. In general, a system is very effective if its precision is great.

Recall: Measuring the sensitivity score in forecasting the invasion files is done by the calculation of metrics recall. The purpose of the evaluation was to determine the prediction range when true and false rates were present. Therefore, using Eq. 6.8, the sensitivity metrics have been verified.

$$\mathrm{Re}\, call = \frac{R_p}{R_p + C_n} \tag{6.10}$$

Eq. 6.8, which validates the parameter precision, has been used to determine the maximum positive score that may be obtained in detecting the intrusion function. Additionally, the mean of all anticipated positive instance has been measured.

F-measure: To determine the average of the prevention rate and tracking range, the F-measure is calculated. Calculating the system's F-measure requires knowledge of its precision and sensitivity score. The formula for calculating the F-score is given in Eq. 6.9.

$$F - measure = 2 \times \frac{R_p \times C_n}{R_p \times C_n} \tag{6.11}$$

where R_p denotes the recall score and C_n denotes the precision score.

6.3.1 Comparison assessment

Software-Defined-Network based Flow ML (SDN-FM) [25], MENSA [26], SDN (NSL-KDD) [24], D-PSM (NSL-KDD) [27], and D-PSM (CICIDS) [27], Deep Learning-based Deep Belief Network (DLbDBN) [30], Support Vector Machine (SVM), Azure Machine Learning-based Multi-Layer

Perceptron (ML-MLP) [28], and Meta-Classification Approach based on Azure Machine Learning (MCAbAML) [29], Fully Connected Long Short Term Method (FC-LSTM) [35], Convolution based Long Short Term Analysis (CbLSTA) [31], Auto-encoder Framework (AF) [32], Deep neural Model (DNM) [33], and Recurrent Neural Model (RNM) [34] when compared with this models our proposed KbDBIF's improves the accuracy. The recommended model has been used to quantify the improvement score in predicting intrusions by deep neural models (DNM) [33] and recurrent neural models (RNM) [34] (Table 6.2).

When compared to previous models, KbDBIF's maximum accuracy for the NSL-KDD dataset was 99.8%, improving the detection score by 1% in the proposed novel. Furthermore, the calculated sensitivity rating is 99.8%; the recall rate has increased by 5% with the suggested KbDBIF, compared with other existing approaches. It should be mentioned that the CICIDS data has an implementation time of 1.57 seconds, whereas the NSL-KDD data has 5.27 seconds (Table 6.3).

A comparative analysis shows that developed model performed better in terms of consistency than the current models. Moreover, a case study is

Table.6.2 Comparison statistics of KbDBIF

	Comparison Assessment						
	KbDBIF						
Metrics	*SDN-FM*	*D-PSM (CICIDS)*	*D-PSM (NSL-KDD)*	*SDN (NSL-KDD)*	*MENSA*	*Proposed (NSL-KDD)*	*Proposed (CICIDS)*
Accuracy (%)	82	98.95	98.77	99.1	99.4	99.8	99.7
Precision (%)	91	95.82	98.1	99	95.82	-	98.8
Recall (%)	79	95.81	92.29	74	95.81	-	99.9
F-measure (%)	82	95.81	95.11	84.9	95.81	98.3	99.4

Table 6.3 Comparison Statistics of BENM

	CICIDS				*NSL-KDD*			
Methods	*Recall*	*F-score*	*Accuracy*	*Precision*	*Recall*	*F-score*	*Accuracy*	*Precision*
CbLSTA	97	94	93.6	93	96.5	96	96.2	96.4
AF	96	95	95.1	94.9	95.5	95.4	95.3	95
DNM	95.3	94.8	95	94.6	95	95.3	95	94.8
RNM	96.3	95.6	96	96	96.5	94	94	94.2
FC-LSTM	96.8	96	96.3	96.2	96.3	95.8	95	95.2
Proposed	100	99.42	99.7	99.73	98.4	97.9	98.4	97.46

employed to confirm the functionality of the built model. For CICIDS data, the recommended model's accuracy was 99.7%, and for NSL-KDD data, it was 98.4%. Moreover, the dual dataset's low error rate of 0.0152 and 0.0028 was attained.

6.3.2 Discussion

Based on the comparison evaluations, the current KbDBIF model has proven to perform the best out of all the models that were examined. This has confirmed that the planned methodology in the network application for identifying unauthenticated characteristics is robust. The BENM model that has been suggested is designed to eliminate malevolent characteristics from the dataset and offer ongoing network surveillance. To validate the stability score, the created model's results are also computed and compared with those of other models. The comparative analysis shows that the developed model outperformed previous methods in producing results. As a result, performance estimates for the developed model are also given for both the NSL-KDD AND CICICDS datasets. Finally, a comparison between the findings and the present model is made in order to show how much the performed model has improved and to determine the improvement %. The effectiveness of the provided model includes both databases is necessary to evaluate the model's importance and the requirement for preventive applications. Figure 6.5 displays the NSL-KDD AND CICICDS performance (Table 6.4).

Measured metrics include the model's accuracy, precision, recall score, and F-score. The CICIDS dataset produced better results than the NSL-KDD

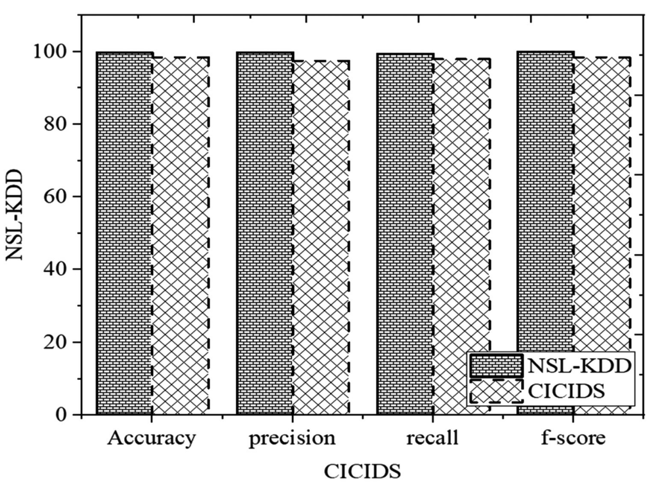

Figure 6.5 Performance of CICIDS and NSL-KDD

Table 6.4 Performance validation of proposed KbDBIF and BENM

		KbDBIF		*BENM*
Metrics	*CICIDS*	*NSL-KDD*	*CICIDS*	*NSL-KDD*
Accuracy (%)	99.7	99.8	99.7	98.4
Recall (%)	99.9	99.8	99.42	97.9
Precision (%)	98.8	99.8	99.73	97.46
F-measure (%)	99.4	99.8	100	98.4

dataset. Using the CICIDS dataset, the suggested model yielded excellent results of 1.0, 99.73%, 99.42%, and f-measure for accuracy, precision, recall, and accuracy. Moreover, the 0.00288 error rate in the CICIDS dataset was rather low. Conversely, the model developed with the NSL-KDD dataset produced excellent results: 98.4% accuracy, 97.46% precision, 97.9% F-score, and 0.9846 recalls. In comparison to the baseline models, the proposed innovation, KbDBIF, improved its recognition score by 1% and achieved the highest accuracy of 99.8% for the NSL-KDD data set. Additionally, the sensitivity score is assessed at 99.8%; the suggested KbDBIF maximizes the recall rate by 5% when compared to different existing approaches.1.57 and 5.27 seconds, respectively, are the stated execution times for the CICIDS and NSL-KDD data.However, compared to the NSL-KDD datasets, the CICIDS data has shown shorter execution times. Less features than the NSL-KDD databases are the cause of this.

6.4 CONCLUSION AND FUTURE WORK

In this study for the network application, a novel KbDBIF has been built to forecast the present intrusion in the wireless system. As a result, the NSL-KDD and CICIDS databases are used to validate the developed model. Furthermore, using the krill herd functions will provide the best results in terms of identifying the infiltration traits. In network applications, a unique hybrid BENM model guards against hostile activity and gives network security. Using a login method also makes continuous network monitoring easier. The two datasets that are utilized for verifying the model are CICIDS and NSL-KDD. Additionally, the approximations and comparisons with other existing approaches' results are provided for the suggested model. A comparison investigation reveals that the created model outperformed existing models in terms of stability. Furthermore, a case study is used to verify how the constructed model functions. The accuracy of the suggested model was 99.7% for CICIDS data and 98.4% for NSL-KDD data Furthermore, the

low error rate of 0.0152 as well as 0.0028 was obtained for the dual dataset. Therefore, the model being offered enables extreme safety in network applications by disregarding the harmful parts in the dataset and providing ongoing monitoring using a login mechanism.

Therefore, the model that was created is appropriate for network applications that predict harmful characteristics. In the future, network users will be able to preserve their privacy range by creating preventive mechanism-based optimal deep features for network applications. These problems will be lessened and the method of prediction will be automated by creating a harmful feature set model in conjunction with the suggested remedy.

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Chapter 7

Using the fuzzy analytic hierarchy process for selecting a closed sociotechnical environment for autonomous vehicle testing in the world of Industry 6.0

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7.1 INTRODUCTION

The automobile is currently undergoing an evolutionary metamorphosis in which automated capabilities such as adaptive cruise control (ACC), collision avoidance, and lane departure detection are becoming the building blocks for autonomous driving. The implementation of enabling technologies that support autonomous driving has gradually been incorporated into the framework of the automobile over the past years. This has allowed for automated driving system functions to be adopted by the drivers in current market vehicle models.

The remainder of this chapter is organized as follows. The rest of Section 1 provides an overview of autonomous vehicle deployment and its lack of emphasis on site selection. In addition to this, the framing of site selection as a multi-criteria decision analysis problem is presented through theory and application methodology of the fuzzy analytical hierarchy AHP. Results and discussion of findings from utilizing Fuzzy AHP are presented Section 2. Concluding remarks and potential future work are posed in Sections 3.

7.1.1 Autonomous vehicle deployment

Autonomous vehicles (AVs) are a disruptive emerging technology that are revolutionizing the transportation sector, along with other connected sectors including energy, economics, health, political science, and law. Composed of an integrated architecture of cameras, light detection radar (LiDAR), sensory-ranged radar, actuators, on-board unit (OBU) software, and global positioning system (GPS) an AV can observe, plan, and act relative to its operational environment [1]. Communication between AVs and other sensors such as those in infrastructure will increase environmental awareness [2]. With a complex web of sensors and computing, to ensure the

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safety of AVs within operational environments, different testing regimes are often leveraged to assess their behavioral competencies in unpredictable driving scenarios. Figure 7.1 provides an integrated framework of testing regimes commonly used in the testing and development (T&D) of AVs.

The idea in Figure 7.1 is that the software or autonomy undergoes critical T&D through the use of simulations that consist of high-fidelity representations of the real-world environment (e.g., buildings, people, vehicles, weather, etc.). As the autonomy of the AV matures, physical testing through closed test track and/or closed sociotechnical environments (CSEs) are utilized for real world behavioral assessment. CSEs provide the closest experience to city environments in physical testing before complex operational environments in open sociotechnical environments (OSEs) are used. OSE testing is where entire cities are used as T&D sites. This is because AVs, at this instance in the T&D process, have matured to the point where they may be deemed safe to operate within these complex driving settings.

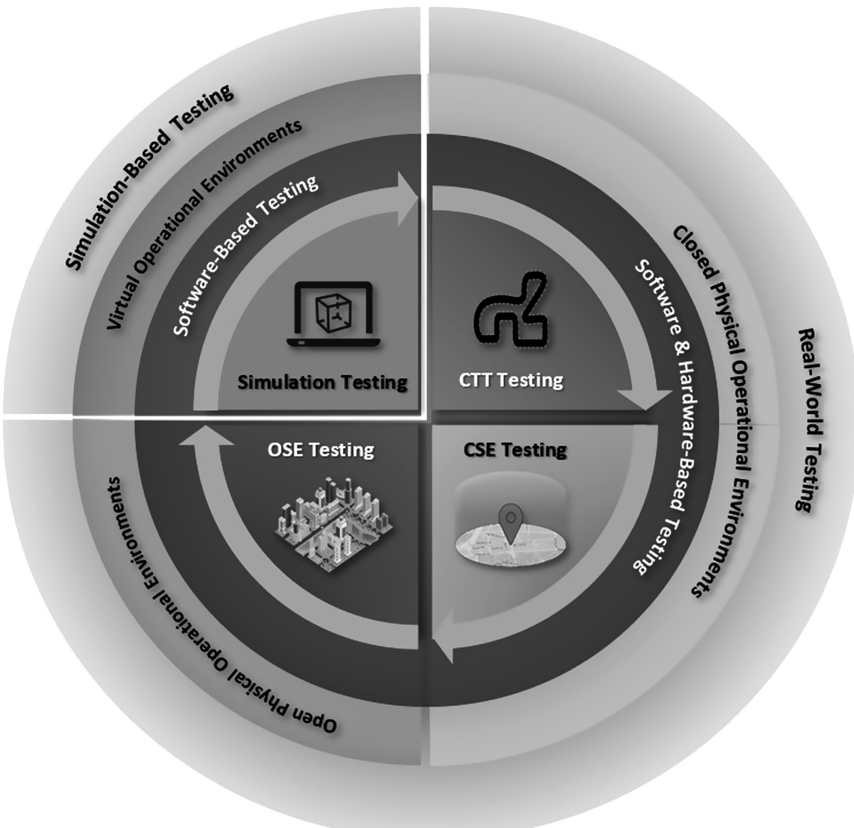

Figure 7.1 Integrated framework of AV testing regimes in alignment with test environments

Though not considered in most AV T&D processes [3, 4], one of the most sensible of these testing regimes may be AV testing in CSEs. A CSE is a constructed environment, a “miniature city”. Attributes of CSEs, such as relatively low flow of people and vehicles, make them a useful testbed for AVs and may help to overcome the distrust between AVs and the public [5–8]. This concept has gained traction, with some AV research and development (R&D) studies using various CSEs such as universities [9–11], airports [12–16], theme parks [17], and military bases [18–21].

The operational domain during AV T&D is a vital facet within the lifecycle of AVs, as not only does the operation domain affect AV performance, but the AVs also have an impact on their operational domain. In observing Figure 7.1, once CTT is completed and CSE testing is initiated, the number of possible operational testing domains for AV T&D increases substantially based on AV maturity since CSEs possess varying levels of driving complexity within their transportation spaces.

With emphasis in literature focused on operational environment conditions, there seems to be a lack of sensible alignment between AV capabilities (i.e., technology readiness level (TRL)) and ethical operational testing domains (EOTDs). A EOTD is a testing environment that is well suited to the current capability/TRL of an AV while balancing public safety and technological progression. EOTDs can help support safe T&D of AVs and improve attitudes amongst the public, thereby improving adoption of AVs. Sensible alignment of AV capabilities to EOTDs can be accomplished by allocating more attention to the test site selection of AVs. Figure 7.2 provides a conceptual depiction of the alignment of AV capabilities with EOTDs. There are numerous CSEs that provide varying degrees of complexity, but

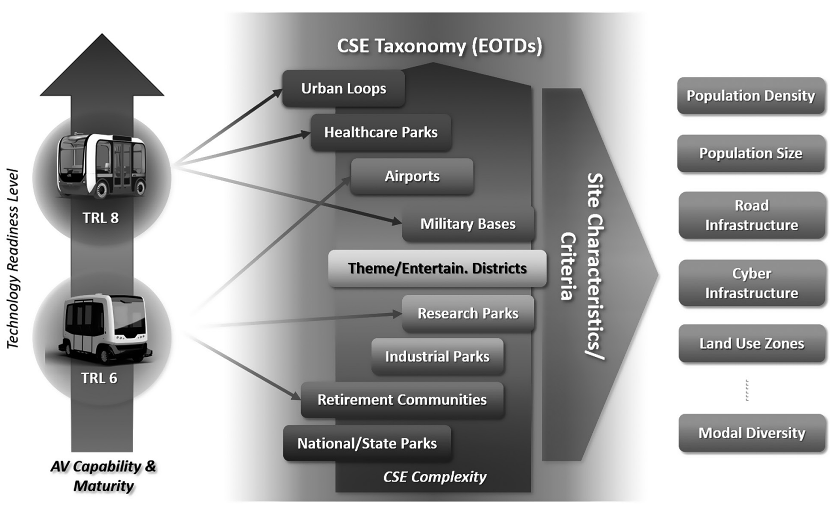

Figure 7.2 Alignment of AV capabilities with potential EOTDs

there is the challenge of aligning these environments to AV capability levels. The intent in Figure 7.2 is to have AVs, as they mature, use more complex CSEs for T&D to allow for seamless transition of AVs into OSE testing. This alignment or selection will need to be driven by various CSE or test site criteria (as seen on the right-hand side of Figure 7.2).

With numerous EOTDs that could be aligned and used to support real-world testing of AVs, the task of site selection can be formulated into a multi-criteria decision analysis (MCDA) problem, where characteristics (Figure 7.2) can be abstracted as criteria, and CSEs, can be viewed as alternative AV test sites to select based on current AV technological capabilities. These pieces of information can be leveraged to form foundational elements of an MCDA known as analytical hierarchy process (AHP). The aim of this chapter is to select a safe and ethical testing site for AVs based on their current capability using the fuzzy variant of the AHP.

7.1.2 Multi-criteria decision analysis

Based on the testbed environments that have been used for the testing, development, and the deployment (TD&D) of AVs, there are various attributes of the CSE indicating how appropriate a CSE is for testing AVs. These various attributes can support a more systematic site selection for the testing of AVs. Due to the complexity of a CSE, and the large number of attributes to be considered, selection of an appropriate CSE is challenging. Framing the selection problem as a multi-criteria decision-making (MCDM) problem supports the sensible selection of a CSE. One such MCDA approach that can assist in this effort is AHP. The AHP is a general theory of measurement used to derive ratio scales from discrete and continuous paired comparisons, considering several factors, dependencies, feedback and making numerical tradeoffs to arrive at a desired decision [22]. The application of using AHP for site selection has been documented extensively within literature with some uses ranging from decision support in convention tourism industry [23] to business site selection [24] to earthen dam site selection [25]. However, AHP nor its variant of Fuzzy AHP, which takes into consideration preferential uncertainties in the decision-making process, has not been leveraged for AV site selection.

7.1.2.1 Fuzzy analytic hierarchy process

In this chapter, the Fuzzy AHP used ten different criteria that are common within transportation and the urban fabric of built environments, to select the most appropriate CSE as a test site for the cognizant development, testing, and potential deployment of AVs. The ten criteria utilized to support in deciding the best CSE given current AV capabilities were *population diversity, population density, population size, road infrastructure, cyber-based*

infrastructure, fueling infrastructure, land use zone diversity, CSE size, traffic flow patterns/composition, and *modal diversity.*

Twenty CSE alternatives were grouped into ten categories: *university campuses*, *retirement communities/villages*, *theme parks/entertainment districts*, *military bases*, *industrial parks*, *research parks*, *airports*, *urban loops/beltways*, *healthcare/medical districts*, and *national parks*. Within each of these categories additional grouping was applied based on similar *population sizes* and *CSE size (land area)*. The ten criteria were crossed and aligned with each of the ten CSE categories as shown in Figure 7.3. Figure 7.3 provides a comprehensive depiction of the analytical hierarchy structure used within this chapter to perform the Fuzzy AHP. Within this analytical hierarchy structure, the overarching goal or objective was to successfully select the most appropriate or safest CSE for AV development, testing, and deployment based on the current level of AV capabilities. Addressing this objective was achieved by considering ten common criteria (or attributes) of a given built environment that were thought to influence safety of drivers, vulnerable road users, and AVs. These criteria or attributes are tied to each respective CSE, giving each CSE a distinct and inherent level of safety, thereby making some CSEs more conducive for AV TD&D based on the current capability level of AVs, hence the systematic approach to AV test site selection.

Within each of the ten CSE categories there is some level of variability, resulting in a total of 20 distinct CSEs used in this decision-making framework. Due to the ambiguity of certain evaluation criteria (i.e., population size, road infrastructure, and cyber-based infrastructure), fuzzy numbers, in the form of the function $M = (l, m, u)$ were used as the general form for preferential linguistics scaling [26, 27] as depicted in Table 7.1. Table 7.1 provides not only a preferential linguistic-based scaling on the right-hand side of the table, but it also shows how this linguistic-based scaling through triangular fuzzy numbers aligns with the traditional rating scale of Saaty's crisp number scale.

Determination of preferences between criteria was facilitated by a pairwise comparison matrix. Valuation between criteria in the matrix was accomplished by using the fuzzy-based linguistic scale in Table 7.1. Additionally, pairwise comparison of criteria also required the application of the triangular fuzzy numbers in Table 7.1 in reciprocal form ($a_{j,i}$) which was achieved through Equation 7.1. Two Fuzzy AHP models, one with five and the other with ten criteria, were constructed.

$$M^{-1} = \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l} \right) \qquad 7.1$$

Once pairwise comparisons between criteria were complete, criteria weights were determined using the geometric mean approach as prescribed by [28].

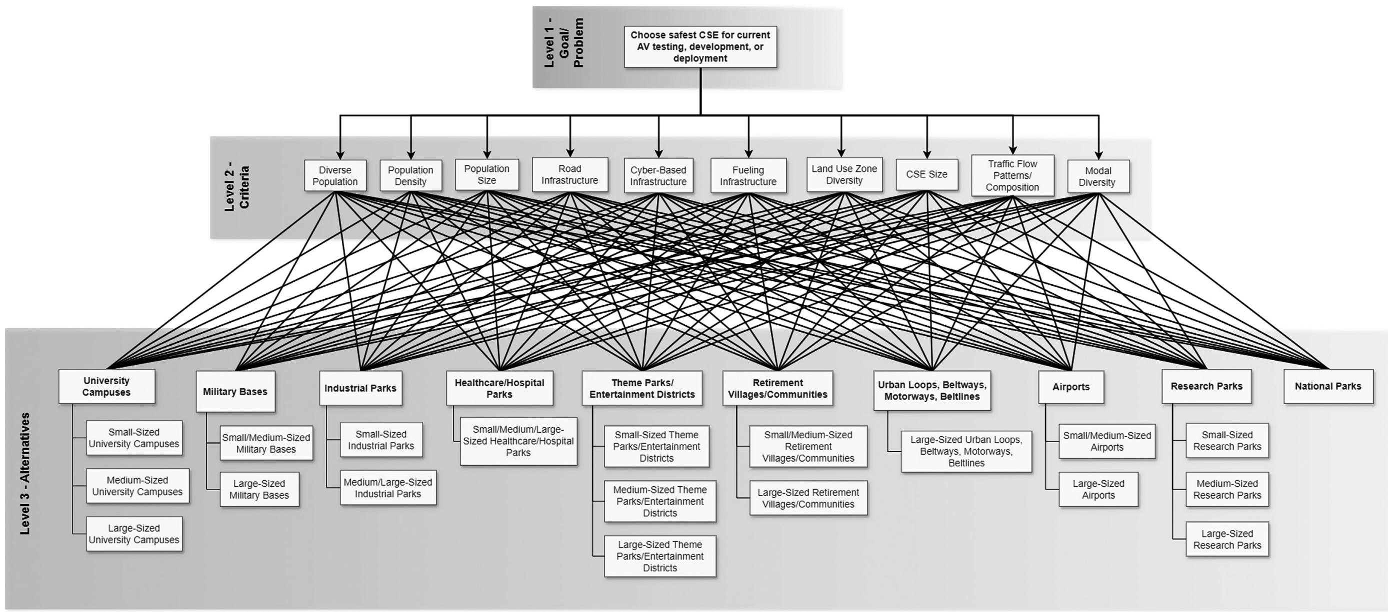

Figure 7.3 Hierarchical structure of the alignment of objective to potential CSE alternatives through analytical hierarchy process

Table 7.1 Linguistic scale aligned with Saaty scale of relative importance [26]

Saaty Scale of Relative Importance	*Level of Importance*	*Triangular Fuzzy Number*
1	Equally Important	(1,1,1)
2	Equally Plus Important	(1,2,3)
3	Weakly Important	(2,3,4)
4	Weakly Plus Important	(3,4,5)
5	Fairly Important	(4,5,6)
6	Fairly Plus Important	(5,6,7)
7	Strongly Important	(6,7,8)
8	Strongly Plus	(7,8,9)
9	Absolutely Important	(9,9,9)

$$r_i = \left(\left(\prod_{i=1}^{n} l_i \right)^{\frac{1}{n}}, \left(\prod_{i=1}^{n} m_i \right)^{\frac{1}{n}}, \left(\prod_{i=1}^{n} u_i \right)^{\frac{1}{n}} \right) \times \left(\sum_{j=1}^{m} M \right)^{-1} \qquad 7.2$$

Equation 7.2 produces a geometric mean in the form of a triangular fuzzy number. However, for the application of making a judgement on deciding the appropriate CSE alternative, the fuzzy weights from Equation 7.2 were defuzzified to crisp numerical values. Defuzzification of the fuzzy geometric mean weights into an individual weight, w_i, was performed using Eq. 7.3 which was represented as:

$$w_i = \frac{l_i + m_i + u_i}{3} \qquad 7.3$$

Defuzzified weights, w_i were normalized. Checks of each of the pairwise comparison matrices in the two Fuzzy AHP models were performed using the consistency index (C.I.).

The normalized score, $S_{norm.}$ in conjunction with the defuzzified weights from each criterion, w_i, were used to determine the combined decision score for each criterion.

$$S_i = \sum_{i=1}^{m} w_j S_{norm.} \qquad 7.4$$

The CSE which maximized the combined score was selected. Table 7.2 provides a list of the 1st-, 2nd-, and 3rd-ordereffect criteria along with the description and corresponding source justifying their use as decision criteria. Within Table 7.2 criteria a total of five criteria (i.e., population density, road infrastructure, land use zones, traffic flow patterns/composition, and

Table 7.2 Criteria used in Fuzzy AHP, description, order of effect, and citation proposing its effect on AV accidents

Criteria	*Description*	*Order Effect*	*Citation Source*
Population Diversity	Number of different social groups that can inhabit a given CSE	2nd Order	[29, 30]
Population Density	Number of people that inhabit or within the entire acreage or spatial dimension of the CSE. (people per sq mi.).	1st Order	[31–33]
Population Size	Number of people that use or inhabit the CSE in question.	2nd Order	[34]
Road Infrastructure	Prevalence of road infrastructure including signs traffic signals, bicycling infrastructures, walking infrastructure, etc.	1st Order	[29, 31, 33, 35–37]
Cyber-Based Infrastructure	Extensiveness of cyber infrastructure including roadside units (RSUs), 5G towers, traffic sensors (e.g., cameras, induction loops, pedestrian detectors, etc.), and information kiosks (i.e., physical/ digital)	2nd Order	[31]
Fueling Infrastructure	Number of different fuel infrastructure stations that exist within a CSE.	3rd Order	-
Land Use Zones	Complexity or # of land use zone types that exist within a CSE.	1st Order	[31, 33, 37]
CSE Size	Area of a given CSE (sq mi.)	3rd Order	-
Traffic Flow Patterns/ Composition	Complexity/types of vehicles that enter or leave a CSE, excluding non-motorized mobility such as bicycles, e-scooters, etc.	1st Order	[30, 38, 39, 40]
Modal Diversity	Number of modes of mobility that are supported in or by the CSE. This can be private mobility, mass transit, micro mobility services (e-scooters, shared bikes, segways, etc.), etc.	1st Order	[30, 33, 39]

modal diversity) were thought to have a direct impact on AV accidents. On the other hand, three criteria (i.e., population diversity, population size, cyber-based infrastructure) were deemed to have an indirect influence on AV accidents while two criteria (i.e., fueling infrastructure and CSE size) seemed to have tertiary effects on the occurrence of AV or vehicular-based incidents making them 2nd- and 3rd-order effect criteria; respectively. Placement of these criteria into their respective order of effects in Table 7.2 was backed by existing, extensive transportation studies performed in literature.

With the delineation of 1st-, 2nd-, and 3rd-order factors that influence AV accidents, two Fuzzy AHP models were created, with the first model considering only first-order effect criteria and the second considering 1st-,

2nd-, and 3rd-order effect criteria. Two models were created for the purpose of assessing changes in the best or most appropriate CSE(s) given consideration and inclusion of specific criteria.

Following the demarcation of criteria into 1st-, 2nd-, and 3rd-order criteria, the process of collecting all pertinent data relative to each criterion for each CSE was conducted. The data collection process consisted of a three-step approach consisting of CSE binning, detailed CSE data gathering, and cross-criteria sorting. CSEs were binned with the ranges from Table 7.3 into either small, medium, or large. With CSEs having conflicting data values within respective criteria, Table 7.3 acted as a categorical bin allowing for CSEs to be sorted strictly based on the criteria of population size and CSE size. Ranges for the subgrouping were arbitrarily selected based on data values that were observed as each of the criteria values for all CSEs were collected.

Once CSE binning was completed, detailed CSE data gathering was performed. Table 7.4 provides a list of features that were of interest for data gathering and methods of measure used during the detailed data gathering phase. In Table 7.4, in respect of each criterion, features within each CSE were assessed in the form of the framed questions seen in the "Built Environment Features of Interest" column. The intent behind these queries was to understand the level or extent to which certain features were prevalent for a given CSE, attributing to its complexity as a built environment for AV TD&D. These questions were answered through a combination of subjective (Likert scale, anecdotal/empirical data, etc.) and objective (census data, AV accident data, etc.) modes of measure as seen in the rightmost column "methods of measure". Data from the detailed data gathering phase was used as representative data values which were normalized relative to criteria values observed in the environment from [29] and multiplied by the criteria weights.

Table 7.5 presents the data for each of the criteria using methods presented above. The data values presented in Table 7.5 are representative of the raw data values obtained through the three-step approach described previously. However, one aspect of note is that due to the variation in data specific to certain CSE criteria (or attributes) a range of values were found during the detailed data gathering certain criteria, requiring two additional Fuzzy AHP models to be constructed. These two additional models considered the

Table 7.3 Ranges used to group CSEs within each CSE taxonomy as subgroups

	Criteria & Criteria Ranges	
CSE Subgroup	*Population Size*	*CSE Size*
Small	< 10,000 people	< 0.5 sq mi.
Medium	10,000–50,000 people	0.5–5 sq mi.
Large	> 50,000 people	> 5 sq mi.

Table 7.4 Features of interest in gathering detailed data on CSEs

Criteria	*Built Environment Features of Interest*	*Methods of Measure*
Population Diversity	Number of unique social groups occupy the CSE	Number of people that may inhabit the CSE space
Population Density	Number of people per unit of area within the CSE	Census Data or derived from population size and CSE size data website sources
Population Size	Number of individuals or people typically within or inhabiting the CSE at any given one point in time	Census Data or derived population data from website sources
Road Infrastructure	How extensive is signage for guiding AVs? How common are the presence of signalized traffic signals? How pervasive are transit stops for various modes? How common are traffic safety systems such as ballards, construction cones and barriers, construction fencing, etc.? How prevalent are buildings setbacks from the roadway? How extensive is walking infrastructure? How common is cycling infrastructure within the CSE? How extensive are civil structures such as railways, overpasses/bridges, barriers/walls, tunnels, etc.? How prevalent are uncommon features such as on-street parking, obstructive vegetation, etc.?	Use of Likert scale for each feature ranging from 0 to 3, where: • 0 = nonexistent road infrastructure • 1 = low level of road infrastructure • 2 = moderate level of road infrastructure • 3 = high level of road infrastructure Scores were averaged across features to give an overall road infrastructure score.
Cyber-Based Infrastructure	How widespread are cyber-physical assets such as cameras and sensors? How pervasive are 5G networking capabilities? How extensive are WiFi networking capabilities? How common are cyber-based tools such as software-based platforms/services for daily operations, environment-wide databases, and other integrated cyber-based workflows used within the functioning of CSE?	Cellular[a]/5G[b] network coverage maps and Google Street View. Use of Likert scale for each feature ranging from 0 to 3, where: • 0 = nonexistent cyber-based infrastructure • 1 = low level of road infrastructure • 2 = moderate level of road infrastructure • 3 = high level of road infrastructure Scores were averaged across features to give an overall cyber-based infrastructure score.
Fueling Infrastructure	Number of fueling infrastructures available on-site	Combination of website sources and Google Maps/Earth observation
Land Use Zone Diversity	How numerous are the land use zone patterns?	Count of land use zones identified in literature
CSE Size	Area of the CSE	Combination of website sources and Google Maps/Earth observations
Traffic Flow Patterns/ Composition	Number and types of vehicles	Combination of conceptual counts of vehicles and Google Maps/Earth observations
Modal Diversity	Number of modes of transportation present for inhabitants	Combination of website sources and Google Maps/Earth observations

[a] https://www.nperf.com/en/map/US/-/3255.Verizon-Wireless/signal/.
[b] https://wigle.net.

Table 7.5 Raw data values for all criteria and all CSE alternatives

CSE Alternatives	*Pop. Div.*	*Pop Dens. (min)*	*Pop Dens. (max)*	*Pop Size (min)*	*Pop Size (max)*	*Road Infra.*	*Cyber Infra.*	*Fueling Infra. (min)*	*Fueling Infra. (max)*	*Land Use Div. (min)*	*Land Use Div. (max)*	*Size (min)*	*Size (max)*	*Traffic Flow (min)*	*Traffic Flow (max)*	*Modal Div. (min)*	*Modal Div. (max)*
S-Univ	5	5,862	14,505	2,042	5,065	1.5	2	1	1	3	7	0.181	0.467	8	8	8	8
M-Univ	5	8,858	64,530	12,987	33,908	2.5	2.5	3	3	8	8	0.583	1.925	10	10	9	9
L-Univ	5	7,604	208,420	61,695	80,895	3	3	3	3	7	7	0.357	8.113	11	11	9	9
S/M-Retire	4	504	4,868	2,450	28,385	2	2	2	2	5	5	1.875	4.844	8	8	8	8
L-Retire	4	2,422	2,422	79,077	79,077	3	2	2	2	7	7	9	32.65	8	8	6	6
S-Theme	3	19,088	30,575	1,223	3054	2.5	2	1	1	11	12	0.04	0.381	6	9	7	7
M-Theme	3	10,052	165,468	21,902	30,000	3	2	2	3	6	6	1	2.656	6	9	7	10
L-Theme	3	4,070	4,070	175,000	175,000	2.5	3	2	2	9	9	43	43	6	6	9	9
S/M-Military	5	25	378	2,872	16,026	2	2	1	2	7	8	0.035	0.035	9	9	9	9
L-Military	5	507	163,793	107,627	260,000	2	2	2	2	7	8	13.53	334.4	9	9	8	8
S-Industrial	3	1,813	4,000	8,500	9,000	2	2	1	1	2	2	0.298	0.298	5	5	6	6
M/L-Industrial	2	14,883	25,137	10,000	55,000	2.5	1.5	2	2	2	2	0.672	4.688	5	5	6	6
S-Research	6	10,032	10,320	4,838	4,838	2.5	1	1	1	4	4	0.469	0.469	7	7	9	9
M-Research	6	4,163	31,993	14,000	35,000	2	2.5	1	1	5	5	0.5	1.094	7	7	6	6
L-Research	6	5,029	5,029	55,000	55,000	2.5	3	1	1	4	6	6.005	6.005	7	7	10	10
S/M-Airports	6	617	26,251	2,083	43,078	2	2	2	2	2	3	1.344	4.687	6	6	8	8
L-Airports	6	9,881	63,495	73,604	365,825	2	2.5	4	4	6	6	5.907	26.886	6	6	11	11
S/M/L-Medical	7	32,542	198,132	42,000	106,000	3	2	1	1	1	4	0.239	2.102	8	8	9	9
Urban Loop	6	618	193,356	971,933	4,911,084	3	3	4	4	8	8	99.78	4775	8	8	11	11
National Parks	3	3	43	3,905	34,377	2	1	3	3	3	4	8.594	3471	6	6	4	4

minimum and maximum values of the ranges for all criteria that possessed a range, which resulted in a total of four different Fuzzy AHP models:

1) Five 1st-order effect criteria with minimum data values (model 1a),
2) Five 1st-order effect criteria with maximum data values (model 1b),
3) All 1st-, 2nd-, and 3rd-order effect criteria with minimum data values (model 2a), and
4) All 1st-, 2nd-, and 3rd-order effect criteria with maximum data values (model 2b).

7.2 RESULTS AND DISCUSSION

The approach described was used in developing the criteria pairwise comparison matrices. Model validation was achieved through consistency checks of the pairwise comparison matrices. A total of four sets of rankings of CSE alternatives were generated corresponding with the four Fuzzy AHP models.

7.2.1 Criteria pairwise comparison matrix results

In order to understand the impact of considering different criteria on AV site selection, two criteria pairwise comparison matrices were developed. The first criteria pairwise comparison matrix only considered first-order effect criteria (Table 7.6). Within Table 7.6 it can be observed that among the first-order effect criteria, population density, road infrastructure, and traffic flow patterns/composition are the most important criteria when compared to other first-order effect criteria due to its higher preference

Table 7.6 Criteria pairwise comparison matrix considering only first order effect criteria

	Pop. Dens.	*Road Infra.*	*Land Use Zone Div.*	*Traffic Flow*	*Modal Div.*	*Defuzzified Weights* (w_j)
Population Dens.	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,2,3)	**0.2415**
Road Infras.	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,2,3)	**0.2415**
Land Use Zone Div.	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(1,1,1)	(1,1,1)	(1,2,3)	**0.1751**
Traffic Flow Patterns	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(2,3,4)	**0.2269**
Modal Div.	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(1,1,1)	**0.1150**

or fuzzy number scores. These first-order effect criteria are additionally affirmed through [41] who used AHP to assess city readiness for connected and autonomous vehicles, finding that physical infrastructure is the most important criteria according to transport policy makers and service providers, infrastructure operators, transport researchers, and users of different transport modes. On other hand, modal diversity was seen to be the least important first-order effect criteria in selecting the safest CSE for TD&D of AVs. The second matrix included 2nd- and 3rd-order effect criteria in addition to the first order effect criteria (Table 7.7). In Table 7.7, the most important criteria that influenced the selection of a safe CSE for AV TD&D were population density, traffic flow patterns/composition, while the least important was fueling infrastructure which was a 3rd-order effect criterion. Defuzzified normalized weights are also included in Table 7.7. Table 7.8 shows the normalized values based on the raw data values from Table 7.5, while Table 7.9 shows ranked CSE alternatives from combining defuzzified weights (from Tables 7.6 and 7.7) and normalized values (from Table 7.9) using Equation 7.4.

Consistency checks on each of the criteria pairwise comparison showed that consistency was maintained among preferences in each matrix due to the consistency index (CI) in each matrix being less than 0.1 [22]. The CI for the pairwise comparison matrix that considered first order effect criteria (Table 7.6) produced a CI of 0.0725, while the matrix considering 1st-, 2nd-, and 3rd-order effect criteria (Table 7.7) generated a CI of 0.0835.

7.2.2 Selection of best CSE alternative

Using Equation 7.4, scores for each of the four different Fuzzy AHP models were generated. Scores and corresponding rankings for each of the 20 CSE alternatives within each of the four Fuzzy AHP models are shown in Table 7.9. Through evaluation of results in Table 7.9, across the four different models, results from models 1a and 1b showed that the best CSE for AV TD&D were small-sized research parks when considering first order effect criteria. On the other hand, when considering 1st-, 2nd-, and 3rd-order effect criteria, findings from Models 2a and 2b showed that the best CSE to support AV TD&D were large-sized airports and large-sized research parks; respectively. Models 1a and 1b consider criteria that are highly influential in transportation performance and are commonly seen as parameters or attributes considered in transportation planning and studies. However, the models 2a and 2b consider more systemic criteria that could affect safety in AV TD&D within a given built environment and provide a different set of CSE alternatives which are larger in scale as compared to those proposed by models 1a and 1b. The addition of 2nd and 3rd order effects in models 1a and 1b may have skewed the normalized values of the alternatives in such a way that CSE alternatives typically seen outside in the top three options in models 1a and 1b were suddenly considered top options in models 2a

Table 7.7 Criteria pairwise comparison matrix considering only 1st-, 2nd-, and 3rd-order effect criteria

	Pop. Div.	*Pop. Dens.*	*Pop. Size*	*Road Infra.*	*Cyber Infra.*	*Fueling Infra.*	*Land Use Zone Div.*	*CSE Size*	*Traffic Flow Patterns*	*Modal Div.*	*Defuzzified Weights* (w_j)
Pop. Div.	(1,1,1)	$\left(\frac{1}{9},\frac{1}{8},\frac{1}{7}\right)$	(1,2,3)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(4,5,6)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	(4,5,6)	$\left(\frac{1}{9},\frac{1}{8},\frac{1}{7}\right)$	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	**0.0346**
Pop. Dens.	(7,8,9)	(1,1,1)	(7,8,9)	(1,1,1)	(1,2,3)	(6,7,8)	(2,3,4)	(7,8,9)	(1,1,1)	(1,2,3)	**0.1917**
Pop. Size	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{9},\frac{1}{8},\frac{1}{7}\right)$	(1,1,1)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	(2,3,4)	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	(2,3,4)	$\left(\frac{1}{9},\frac{1}{9},\frac{1}{9}\right)$	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	**0.0256**
Road Infras.	(6,7,8)	(1,1,1)	(6,7,8)	(1,1,1)	(1,2,3)	(5,6,7)	(2,3,4)	(6,7,8)	(1,1,1)	(1,2,3)	**0.1816**
Cyber Infra.	(2,3,4)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(3,4,5)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(1,1,1)	(6,7,8)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(5,6,7)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	**0.0788**
Fueling Infra.	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	(1,1,1)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	$\left(\frac{1}{9},\frac{1}{9},\frac{1}{9}\right)$	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	**0.0150**
Land Use Zone Div.	(4,5,6)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(5,6,7)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(2,3,4)	(6,7,8)	(1,1,1)	(6,7,8)	(1,1,1)	(1,2,3)	**0.1345**
CSE Size	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{9},\frac{1}{8},\frac{1}{7}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	(1,2,3)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	(1,1,1)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	**0.0175**
Traffic Flow Patterns	(7,8,9)	(1,1,1)	(9,9,9)	(1,1,1)	(4,5,6)	(9,9,9)	(1,1,1)	(6,7,8)	(1,1,1)	(1,2,3)	**0.1911**
Modal Div.	(5,6,7)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(6,7,8)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(2,3,4)	(6,7,8)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(5,6,7)	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(1,1,1)	**0.1295**

Table 7.8 Normalized raw values from raw data values (from Table 7.5) for each criteria and CSE alternative

CSE Alternatives	*Pop. Div.*	*Pop Dens. (min)*	*Pop Dens. (max)*	*Pop Size (min)*	*Pop Size (max)*	*Road Infra.*	*Cyber Infra.*	*Fueling Infra. (min)*	*Fueling Infra. (max)*	*Land Use Div. (min)*	*Land Use Div. (max)*	*Size (min)*	*Size (max)*	*Traffic Flow (min)*	*Traffic Flow (max)*	*Modal Div. (min)*	*Modal Div. (max)*
S-Univ	1	0.5831	0.9789	0.0105	0.0258	0.	0.5	0	0	0.5	0.8333	0.0034	0.0142	0.6	0.75	0.6	0.75
M-Univ	1	0.8812	0.7263	0.1511	0.3964	1	0.75	0.6667	0.6667	0.5	0.6667	0.0128	0.0589	0.2	0.25	0.4	0.5
L-Univ	1	0.7564	0	0.7767	1.0017	0	1.	0.6667	0.6667	0.6667	0.8333	0.0075	0.2486	0	0	0.4	0.5
S/M-Retire	0.6667	0.0501	0.4695	0.0158	0.3254	0.5	0.5	0.3333	0.3333	1	0.75	0.0428	0.1484	0.6	0.75	0.6	0.75
L-Retire	0.6667	0.2408	0.2315	1	0.9766	0	0.5	0.3333	0.3333	0.6667	0.8333	0.2087	1	0.6	0.75	1	0.6667
S-Theme	0.3333	0.5982	0.8977	0	0	1	0.5	0	0	0	0	0.0001	0.0116	1	0.5	0.8	1.
M-Theme	0.3333	1	0.2168	0.2656	0.3462	0	0.5	0.3333	0.6667	0.8333	1.	0.0225	0.0813	1	0.5	0.8	0.25
L-Theme	0.3333	0.4048	0.3918	0.8926	0.9822	1	1	0.3333	0.3333	0.3333	0.5	1	0.9978	1	0.5	0.4	0.5
S/M-Military	1	0.0022	0.0326	0.0212	0.1666	0.5	0.5	0	0.3333	0.6667	0.6667	0	0.0010	0.4	0.5	0.4	0.5
L-Military	1	0.0502	0.2253	0.9680	0.9646	0.5	0.5	0.3333	0.3333	0.6667	0.6667	0.3141	0.9364	0.4	0.5	0.6	0.75
S-Industrial	0.3333	0.1802	0.3850	0.0935	0.0764	0.5	0.5	0	0	0.25	0	0.0061	0.0090	0	0	1	0.6667
M/L-Industrial	0	0.7852	0.9252	0.1127	0.6673	1	0.25	0.3333	0.3333	0.25	0	0.0148	0.1436	0	0	1	0.6667
S-Research	0.5	0.9881	1	0.0464	0.0229	1	0	0	0	0.75	0.5	0.0101	0.0143	0.8	1	0.4	0.5
M-Research	0.5	0.4140	0.8906	0.1641	0.4104	0.5	0.75	0	0	1	0.75	0.0108	0.0334	0.8	1	1	0.6667
L-Research	0.5	0.5002	0.4852	0.6907	0.6673	1	1	0	0	0.75	1	0.1390	0.1840	0.8	1	0.2	0.25
S/M-Airports	0.5	0.0612	0.9196	0.0110	0.5142	0.5	0.5	0.3333	0.3333	0.25	0.25	0.0305	0.1436	1	0.5	0.6	0.75
L-Airports	0.5	0.9830	0.7316	0.9297	0.9427	0.5	0.75	1	1	0.8333	1	0.1367	0.8242	1	0.5	0	0
S/M/L-Medical	0	0	0.0519	0.5238	0.9965	0	0.5	0	0	0	0.5	0.0048	0.0643	0.6	0.75	0.4	0.5
Urban Loop	0.5	0.0612	0.9545	0	0.0017	0	1	1	1	0.5	0.6667	0	0	0.6	0.75	0	0
National Parks	0.3333	0	0	0.0344	0.4024	0.5	0	0.6667	0.6667	0.5	0.5	0.1992	0.2750	1	0.5	0	0

Table 7.9 Table of rankings based on CSE alternative scores from each Fuzzy AHP model

	Model 1a		*Model 1b*		*Model 2a*		*Model 2b*	
Model Considerations	*1st Order with Minimum Data Values*		*1st Order with Maximum Data Values*		*1st, 2nd, 3rd Order with Minimum Data Values*		*1st, 2nd, 3rd Order with Maximum Data Values*	
Rankings	***Scores***	***Alternatives***	***Scores***	***Alternatives***	***Scores***	***Alternatives***	***Scores***	***Alternative***
1	0.8390	S-Research	0.8549	S-Research	0.7001	L-Airport	0.7490	L-Research
2	0.7310	L-Airport	0.7894	L-Research	0.6952	S-Research	0.7273	M-Research
3	0.7063	M-Theme	0.7707	M-Research	0.6826	L-Theme	0.7145	S-Research
4	0.7048	S-Theme	0.6867	S-Theme	0.6733	L-Research	0.6530	S-Theme
5	0.6982	L-Research	0.6479	M-Univ	0.6679	M-Research	0.6380	M-Univ
6	0.6924	M-Research	0.6387	S-Univ	0.6617	M-Theme	0.6222	L-Theme
7	0.6705	L-Theme	0.6219	S/M-Retire	0.6419	S-Theme	0.6151	S-Univ
8	0.6332	M-Univ	0.5946	L-Theme	0.6156	M-Univ	0.6006	S/M-Retire
9	0.5899	M/L-Industrial	0.5863	S/M-Airport	0.5231	M/L-Industrial	0.5911	L-Airport
10	0.5131	S/M-Retire	0.5860	L-Airport	0.4959	S/M-Retire	0.5708	S/M-Airport
11	0.4752	S/M-Airport	0.5416	M/L-Industrial	0.4767	L-Retire	0.5364	L-Military
12	0.4352	National Park	0.5174	Urban Loop	0.4675	S/M-Airport	0.5272	Urban Loop
13	0.4335	S-Univ	0.4916	L-Military	0.4535	L-Military	0.4961	L-Retire
14	0.4260	L-Retire	0.4487	L-Retire	0.4457	S-Univ	0.4896	M/L-Industrial
15	0.4094	L-Military	0.4163	S/M-Military	0.4299	L-Univ	0.4303	S/M-Military
16	0.3748	S/M-Military	0.3697	M-Theme	0.3837	S/M-Military	0.3983	M-Theme
17	0.3454	L-Univ	0.3278	S/M/L-Medical	0.3751	National Park	0.3513	S/M/L-Medical
18	0.3230	S-Industrial	0.3218	National Park	0.3419	S-Industrial	0.3303	L-Univ
19	0.2385	Urban Loop	0.2904	S-Industrial	0.3049	Urban Loop	0.3040	S-Industrial
20	0.1821	S/M/L-Medical	0.2034	L-Univ	0.2193	S/M/L-Medical	0.2903	National Park

and 2b. Nevertheless, among these alternatives, research parks seem to be unanimously agreed upon across all models as the safest CSE for TD&D of AVs based on their current level of capability.

7.3 CONCLUSIONS

AVs are a promising emerging technology that could extensively transform existing transportation spaces by providing unparalleled benefits. Based on a growing mistrust of AVs, a more sensible approach in their integration within existing transportation systems is needed. One way this could be achieved is through the incorporation of CSEs in the AV TD&D process in unison with closed test track, simulation-based, and open environment-based approaches. CSEs could be leveraged as miniature-sized cities, allowing for a sufficient balance between public safety and continuous technological advancement.

In this study, the multi-criteria decision analysis approach Fuzzy AHP was utilized to frame the complex problem of selecting the most appropriate CSE to support safe AV TD&D. Findings from each model showed that in the case where only first-order effect criteria are considered, the best CSE for AV TD&D is small-sized research parks, suggested by both Model 1a and 1b. On the other hand, when 1st-, 2nd-, and 3rd-order effect criteria are considered, the most appropriate CSE for safe AV TD&D changed to be large-sized airports and large-sized research parks as proposed by Models 2a and 2b; respectively. However, a comparison across all four of the Fuzzy AHP models showed that among the top choices three out of the four models suggested research parks as a common CSE for AV TD&D. Additionally, panning out to investigate the top three choices across all four models, it was shown that small-sized research parks were within the top three choices of each of the four models.

The benchmarking process in the Fuzzy AHP only considered AV accident data from one AV testing region – the San Francisco Bay area (i.e., Downtown San Francisco and Palo Alto). In future work, it will be interesting to observe what CSEs may be chosen if AV incident data from other test site locations are utilized in the benchmarking datasets. With large-scale AV testing and development ongoing in various cities around the world, benchmarking data points could be leveraged to better inform CSE site selection due to a larger sample size of current AV capabilities.

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Chapter 8

ScatterNet-based IPOA for predicting violent individuals using real-time drone surveillance system

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8.1 INTRODUCTION

To lessen the strain of physical labour, video surveillance has recently been mechanised. The amount of automated analysis for identifying and tracking event activity is growing daily. When a person is moving between different camera windows, activity tracking and recognition become quite difficult [1]. In public spaces with limited staff, the automated system is absolutely necessary. The accurate identification of aberrant occurrences the public domain is a challenging task [2]. These anomalous situations, such as fights, accidents, chain snatching, robbery, etc., are designed to be detected by this video surveillance system. Countless cameras have been installed all over the world to protect public safety [3]. These cameras have trouble storing the entire video stream, which includes supplementary data. Incorporating automatic monitoring methods into the current system is now required [4]. Recently, classification approaches have become crucial in the video surveillance problem because numerous monitoring strategies perform poorly [5]. A sample picture frame extracted from the movie is shown in Figure 8.1 [6].

The visible presentation of physiologic, psychological, or mental disorders is considered to be aberrant conduct, which is a widespread social phenomenon in life [7]. Abnormal behaviour, in a wide sense, is conduct that differs from standards and expectations. There are various reasons why people behave abnormally, such as cultural differences, release from misery, lack of thinking or emotion, having a different perspective on the world, and so on. The criteria for aberrant behaviour have been further categorised by psychologists who research it, and now include transgressions of social norms, statistical rarity, emotional suffering, and maladaptive behaviours [8]. A conduct can be labelled abnormal if the majority of the aforementioned requirements are satisfied. Both general deviant behaviours (such as transgressing moral and social norms) and significant deviant behaviours (such as criminal activity, suicide, disputes, and violent occurrences) are examples of common aberrant behaviours. The possibility exists for mild abnormal

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Figure 8.1 Example of a single surveillance video frame

behaviour to progress to severe abnormal behaviour. Therefore, frequent or widespread deviant behaviour will have a negative impact on societal security and stability whether it is serious or general [9]. Given the damage that deviant behaviour causes, it is crucial to increase the effectiveness of social security prevention and control measures, decrease the number of violent injury incidents each year, research the potentially dangerous motivations behind abnormal behaviour, and develop appropriate early warning and intervention strategies [10]. Utilising surveillance has grown in importance as a way to protect the protection of life and property in recent years due to the ongoing expansion of the economy, infrastructure, and population [11]. Without the need for labour-intensive, challenging, and error-prone data labelling, deep learning systems provide a means to automatically extract meaningful and significant spatial and temporal properties from raw data. [12]. Deep learning models may therefore be readily generalised to many scenarios. The excellent performance accuracy of deep learning models in predicting violent persons in many study domains is what drives people to choose them [13].

The following are the chapter's chief contributions:

- This chapter develops a novel SDL for predicting violent individuals with ASIIR dataset. The results of experiments validate the suitability of this strategy for classification tasks involving tiny samples.
- Due to its robustness and efficiency, the suggested SDL model only needs a few parameters and converges quickly during training.
- In some datasets, the model built using our suggested SDL outperforms the most advanced convolutional frameworks in terms of classification accuracy.

- IPOA is utilised in parameter tuning.
- The accuracy, recall, precision, and F1-score are used to assess the results.

The study's remaining portions are organised in the form of shades: The pertinent works are summarised in Section 8.2, the recommended model is briefly explained in Section 8.3, the results and validation analysis are described in Section 8.4, and the summary and finalisation are provided in Section 8.5.

8.2 RELATED WORKS

A solution is proposed by Nguyen et al. [14] to use deep learning on UAVs to develop a system for real-time violence detection. The resolution will concurrently meet several standards, including calculation speed, accuracy, high coverage, model capacity, quick deployment, and object tracking technology; in particular, model capacity, calculation speed, and accuracy fully satisfy real-time deployment's requirement. The performance was ended with weights of just 564.3 KB, 93.69% mAP (0.5), 0.114 FLOPS(B), and a maximum frame rate of 21–22 FPS, according to experimental data.

In the proposed system by Biswas et al. [15], the movement of objects with the proper frame resolution is detected using frame resolution switching and a classifier using a convolution neural network (CNN). Dynamically recording an HD frame allows for the capture of moving suspicious objects. The system takes pictures of less important, low-quality frames. Finally, all frames are subjected to the enhanced gradient-based histogram equalisation technique to offer greater veracity in dubious frames. According to numerous real-time imperial testing, the suggested method successfully uncovers questionable items 98.25% of the time. Additionally, 80% fewer bits of storage is used overall by the system.

Dai and Nagahara [16] in their short paper examine drone platooning control utilising simply the data from a camera that is mounted to each drone. They accomplish this by putting into Use the YOLO (you only look once) deep learning model to exercise real-time objection detection. In order to control each drone in a platoon, a feedback controller that uses proportional-derivative analysis continuously evaluates the relative location of the drone in front. Three drones were used in indoor testing to demonstrate the usefulness of the proposed system.

Object detection and objects categorisation are the two stages of the proposed robust deep learning-based real-time technique by Ranjith et al. [17]. The YOLO-v2 with ResNet-152 approach is used to detect objects and for everyone, builds a bounding box. Additionally, the optimum kernel extreme learning machine (OKELM) is used to categorise the identified items. Additionally, the fruit fly optimisation (FFO) algorithm is used to

adjust the KELM model's weight parameter, improving classification performance. On the benchmark dataset, several simulations were run, and the findings are reviewed from a number of angles. In terms of a number of performance indicators, the testing results demonstrated the superiority of the RDL-RTOD technology over more modern methods.

This article by Rodrigues et al. [18] focused on using deep learning techniques to present a fusion monitor solution composed of three separate algorithms: a lost item detection system, a violent object identification system, as well as a technology that recognises violent encounters between passengers. Using available datasets for COCO and TAO object detection algorithms are latest algorithms like YOLOv5 were developed. Training was done using the MoLa InCar dataset cutting-edge algorithms for violent action detection, including I3D, R(2+1)D, SlowFast, Temporal Segment Networks (TSNs), and Temporal Shift Module (TSM). Finally, it was shown that both approaches operate in real-time using an embedded automobile solution.

A drone for nighttime security with aerial ubiquitous display (AUD) has been created by Kakiuchi et al. [19] to address the issues with the current security robots. The AUD has a projector and an infrared camera to monitor nighttime human activity and provide information to those in need. In order to determine whether the AUD can offer sufficient nighttime security, an experiment was carried out with it in this study. The experiment made it possible to observe events in real time and project information from the air. Additionally, the efficacy of new security techniques utilising the AUD was demonstrated. In the future, labour shortages will be reduced and proper protection techniques will be created if the protection guards are replaced by the AUD to offer protection at night.

Snoun et al. [20] in their study developed a new system of support to help Alzheimer's patients complete their everyday duties on their own. The suggested help systems are split into two sections. A human activity recognition (HAR) module is the first, and it tracks patient conduct. They suggested two HAR systems in this case. The first uses a convolution neural network with 2D skeleton data, while the second uses a 3D skeleton and transformers. The support module in the second component of the assistance systems is responsible for identifying the patient's behavioural anomalies and issuing the required warnings. Here, they added two techniques as well. The first is built using a straightforward conditional framework, while the second uses a reinforcement learning approach. They consequently acquire four separate Alzheimer's patient aid programmes. Finally, using the DemCare dataset, a comparison of the four systems' performance and computational complexity was done.

8.3 PROPOSED METHODOLOGY

This section of the chapter gives specifics on the suggested SDL model. To reiterate, our goal is to create a framework that can forecast violent events

over a range of time periods. This study offers a multi-timescale model that forecasts future trajectories at various timescales with this goal in mind. The goal is to increase understanding throughout a range of timescales. This study incorporates an equivalent model into the framework that recreates the past to further enhance performance. The human pose trajectory is used as the input in this paper.

The pose trajectory reflects the human movements fairly effectively in addition to being compact in nature. Figure 8.2 displays our framework's top-level block diagram. It has two models that, respectively, predict the past and the future. It combines the estimates from the two models at a specific timescale to get a composite estimate at every time instant. As an illustration, the model divides the breakdown of the sequence sub-sequences (of length 3), which it then uses to produce forecasts for timeframe 1 in the future (in our configuration, timeframe 1 indicates time period of three steps). These future predictions are then made for the next three steps in the sub-sequences. To get the forecast for the whole input sequence in the future throughout this time period, these forecasts are concatenated. It flips the input order and sends it to the model for past predictions to obtain the past prediction. Despite having the identical architecture, the two models are trained differently. A anticipated sequence at a given timeline is created by combining past and future forecasts. Finally, all of the forecasts from various timescales are properly merged to produce a final forecast error sequence for the input sequence. When anticipating violent people, it shows higher prediction errors, while typical activity predictions show lower mistakes.

8.3.1 Problem setup

This study uses a set of 25 locations on the human bones that were collected throughout time to describe the trajectory of a human stance. Let $p_j^i(t)=\left[x_j^i(t),y_j^i(t)\right]$ be the coordinates of the image j^{th} point in the stance depiction of i^{th} individual at time t. The position of at time t is i^{th} person is represented as $X_t^i=\left[p_1^i(t),p_2^i(t),\ldots,p_{25}^i(t)\right]^T \in R^{50\times 1}$ and the appropriate anticipated position is shown by $\hat{X}_t^i$. The model receives as input a posture trajectory of a particular length and uses a hierarchical framework to produce predictions at various timescales. The model gives many predictions

Figure 8.2 Process flow for the suggested model

for any time, instant, or timescale because it slides a window across the input signal. To obtain a final prediction at a specific time instant, these various guesses are averaged together. The historical projections are obtained using a similar methodology. To obtain an abnormality score, all of the timeframes' prediction errors are aggregated. Figure 8.3 displays an example of our projected stances [21].

In contrast to the previous three scenes, the first one features a walking action. The stances correspond to the actual and expected positions. For aberrant poses, the model creates significant prediction errors.

8.3.2 Aerial suspicious individuals identification and re-identification dataset

The study suggests the ASIIR dataset [22], which includes photographs of people engaging in a variety of dubious activities and taken at various scales, positions, light levels, blurriness levels, etc. The dataset is gathered in a way that makes it appropriate for a human re-identification task in which suspect persons emerge, vanish, and then resurface in consecutive images – without necessarily engaging in the suspect behaviour. This dataset could pique the curiosity of researchers in deep learning applications for airborne security and safety.

The suggested approach in this study uses a dataset for labelled Identification and re-identification of suspicious individuals in the air to identify suspicious people. The collection consists of 2000 photos, each of which has more than 50 people in it. In total, 51240 (48%) of the 108570 persons in the sample were involved in one or more of the six questionable behaviours, including strangulation, punching, kicking, shooting, stabbing, and sword fighting. According to Fig. 8.4 [22], each individual in the aerial picture has 18 keypoints that are utilised as labels by the network to estimate posture. Twenty-five participants between the ages of 18 and 25 participate in the activities. The Parrot AR is used to record the photographs.

(a) *Walking* (b) *Cycling* (c) *Leaving bag* (d) *Throwing bag*

Figure 8.3 A representation of the suggested model's projected poses

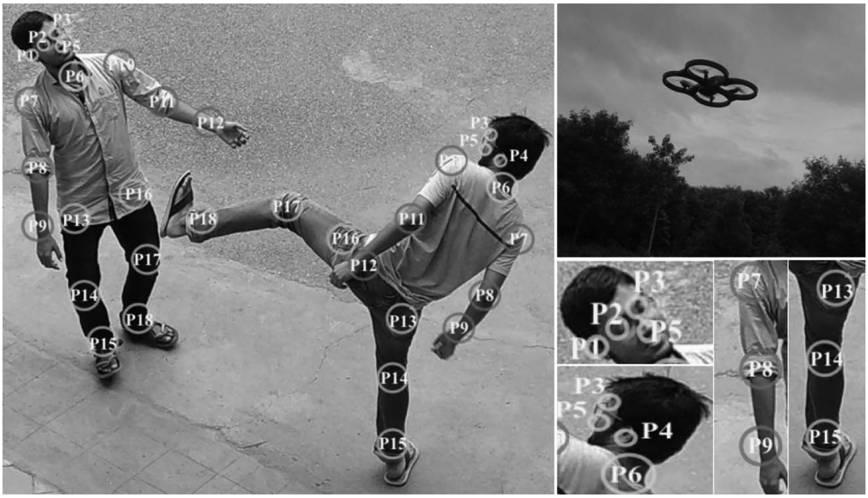

Figure 8.4 The 18 anatomical keypoints that are annotated in the dataset are shown in the image (left)

Drone 2.0 at four different heights: 50, 100, 150, and 200 metres (m). The photographs were taken in a way that allowed one or more people in one frame to eventually fall out of the picture due to the moving drone, hence the dataset is suitable for the re-identification problem and they would then make a comeback in the frame that followed due to (1) drone re-spotting in motion, and (2) drone extends field of view by ascending, causing the subject(s) to reappear in the frames. The process of identifying and reidentifying questionable people from these aerial photos is a very difficult process since the lighting, shadows, resolution, and blurring of the images may all alter the results. The people may also appear in various positions, directions, and scales. Images with the above-described modifications are included in the suggested dataset because they have the potential to drastically modify human appearance and have an impact on the effectiveness of surveillance systems. When trained on a dataset that contains these variances, the SDL network can figure out how to represent them and identify suspicious people despite these changes.

The keypoint is described as follows: The arm area contains the right elbow, right shoulder, right wrist, left shoulder, left wrist, and left elbow. P1 stands for the right ear, P2 for the right eye, P3 for the left eye, P4 for the left ear, P5 for the nose, and P6 for the neck. P13 denotes the right hip, P14 the right knee, P15 the right ankle, P16 the left hip, P17 the left knee, and P18 the left ankle in the leg area. The Parrot AR Drone 2.0 is seen in the figure (right), along with close-ups of a few important landmarks.

Pictures in the top column of Figure 8.5 [22] depict the situation prior to the actual event (in green), People who participated in suspicious behaviour

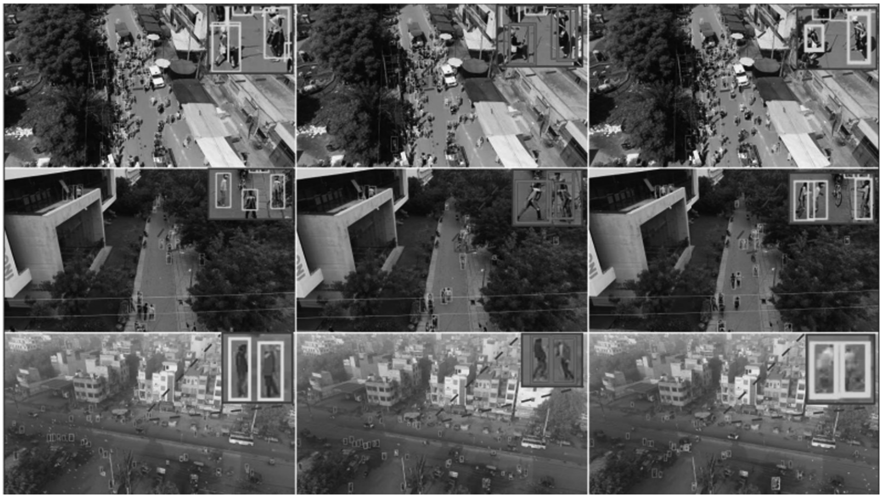

Figure 8.5 The figure depicts three distinct actions: striking, kicking, and sword combat

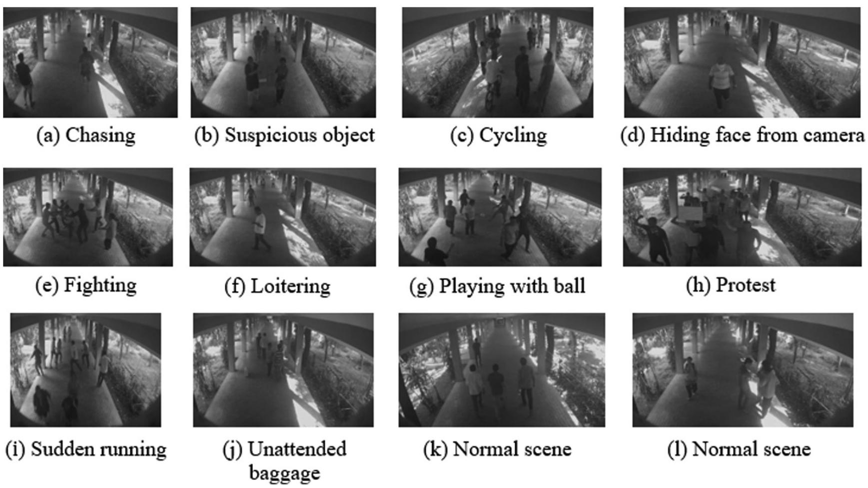

Figure 8.6 Sample images from the proposed ASIIR dataset

were in the second column, as determined by the software, and individuals that the software again identified in the third column. Figure 8.6 [22] displays a selection of photographs from the suggested ASIIR dataset.

8.3.3 Anomaly detection

This portion of the article talks about how to find anomalies during testing. A human's posture trajectory is predicted by the trained model at various

timeframes. As a result, it may make several predictions at once using various scales. To get the ultimate prediction error, using a vote process, these multiple prediction mistakes are combined. The mistakes are compounded as follows by Eq. 8.1 at any moment, instant t:

$$error(t)=\frac{\sum_{j\varepsilon S} L_2^j(t)}{|S|}, \tag{8.1}$$

where S is a collection of timelines with forecasts for the time instant t and $L_2^j(t)$ is the j^{th} layer loss at time t, as in Eq. 3. It should be noted that there may be numerous humans present at any given time, resulting in separate error plots for each individual. In this situation, it requires the most prediction mistakes among all people at a given moment. That is Eq. 8.2,

$$error(t)=\frac{\sum_{j\varepsilon S} \max\{L_2^j(t,p_k),\forall k\}}{|S|}, \tag{8.2}$$

where $L_2^j(t,p_k)$ is the jth layer loss at time t for the k-th individual. In order to find any abnormalities, it is evaluated against a threshold.

8.3.3.1 SDL classification

It is suggested that filter learning be accomplished via a thin network constructed using the Scattering Transform (Figure 8.7) [23]. The following example shows how the procedure can be divided into three steps: (1) to extract the sequence characteristics from the source feature maps or images, a distinctive Strip-Recurrent module is used; (2) input $I^{(i)}(c,u(x,y))$ is filtered by ScatterNet using preset parameters; (3) a learnt weight matrix A is referred to as a scattering transform-based filter learning term; and (4) the filter is used to filter the data.

A) Strip-Recurrent module

In contrast to the feature learning approach using a single bidirectional RNN layer, this study offers by employing two LSTM layers and the Strip-Recurrent module, the feature map is stripped to reveal the input image's sequential features. Suppose $I(c,\boldsymbol{u}(x,y))$ is divided into a number of patches from the feature map or input image, which has the dimensions x, y, and c. $P=\{p_l,m\}$, where l and m are the vertical index, the horizontal index, and their combined number is $L*M$. Think of a patch that is $x_p \times y_p$; *(l, m)*-th patch is described as $p_{l,m} \in R^{x_p \times y_p \times z_p}$. This approach first sweeps every image patch $P_{l,m}(x_p \times y_p \times z_p)$ horizontally provided there is an LSTM layer, $x_p \times y_p$

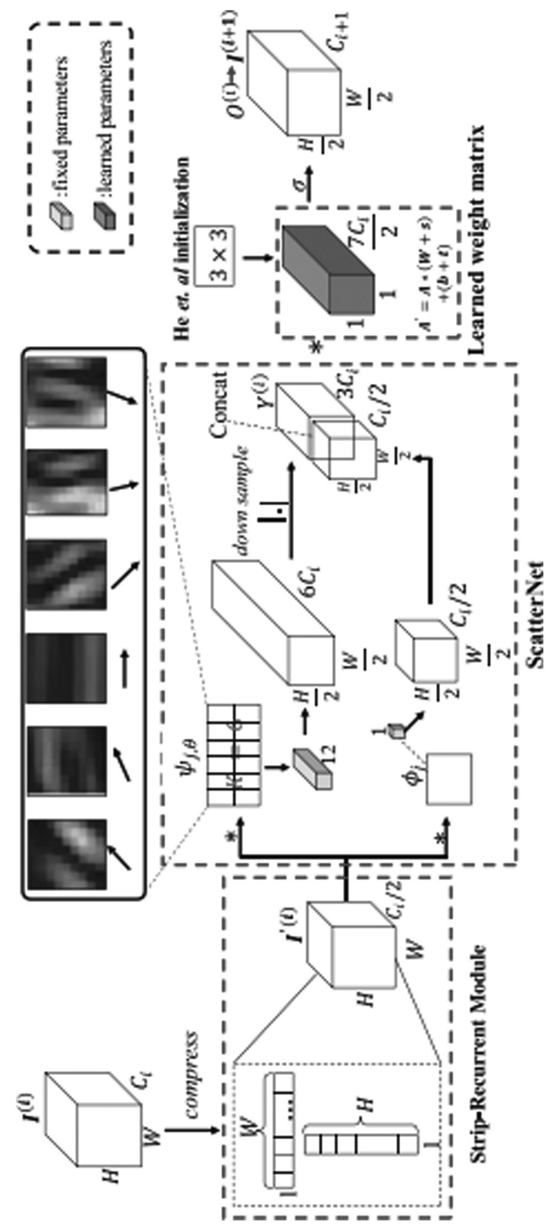

Figure 8.7 The lightweight scattering transform layer's block diagram, showing the learned weight matrix

is set to 1 × 1, then repeats the procedure vertically for the outcomes mentioned above. The entire procedure is defined by the Eq. 8.3:

Input: $I^{(i)}\left(c,B\left(x,y\right)\right)\xrightarrow{split}\left\{p_l,m\right\}$,

for $l = 1, 2, \ldots, L$ and $m = 1, 2, \ldots, M$

Horizontal sweep: H = LSTM $\left(I^{(i)}\left(c,\boldsymbol{u}\left(x,y\right)\right),p_l,m\right)$,
for $l = 1, 2, \ldots, L$

$\left(H,p_l,m\right)$ Vertical sweep: V = LSTM, for l = 1, 2, . . . , M (8.3)

Where H represents the outcome of a horizontal sweep followed by an LSTM layer and V represents the outcome of a vertical sweep is followed by an LSTM layer. Following these two sweep of the permuting and recurrent strip module, the dimension of the source feature map is modified from $H\times W\times C_{in}$ to $H\times W\times C_{out}/2$.

B) Learnable scattering transforms

The fixed filter is used to formulate the scattering transform. The low pass and invariant terms are mixed, the 2D-wavelet transform is largely finished, and the recommended scattering-based method is used to learn the weights assigned to various phrases throughout the mixing process. The dark grey modules in the SDL are designated as weighted matrices with learning parameters, whereas the dingy modules stand in for transformation matrices with predetermined parameters. Prior to the sequence features, the input image or map of features is compressed are extracted using a unique strip-recurrent module $I^{(i)}\in R^{H\times W\times C_i} to I^{'(i)}\in R^{H\times W\times C_i/2}$, then $I^{'(i)}$ filtered through actual and fictitious orient scattering transformations on the bottom branch of the canal from $C_i/2to\left(2K+1\right)C_i/2$, amount of orientations is K. the results from a small sample $I_1^{'(i)}\in R^{H/2\times W/2\times 6C_i}$ the component of orient scattering and the component $I_2^{'(i)}\in R^{H/2\times W/2\times C_i/2}$ of low pass to produce the desired effect $Y^{(i)}$. Finally, to produce the suggested output, it convolves $Y^{(i)}$ utilising the mastered weight matrix A is $O^{(i)}$ as Eq. 8.4:

$$O^{(i)}=\left\{S_pI,U_{p+\lambda}I\right\}\lambda=\sum_{C=0}^{C-1}(I^{'(i)}*\varphi_j+\left|I^{'(i)}*\left(\psi_{j,\theta}\right)_\lambda\right|)*A \tag{8.4}$$

Where dual-tree complex wavelet transform (DTCWT) has been selected as our wavelet filter is ψ_j,θ because it was implemented quickly. The limitation on the number of wavelet orientations K, as well as the fact that the path sequencing is a diagonal matrix handled as an educative weight matrix A, are both drawbacks of this approach that includes two weight factors

$\{a(c),k(c)\}$ corresponding to φ_j and $\psi_{j,\theta}$, each, and a random matrix is used to determine its initial value. Assuming the path is an index factor, the following equation (5) can be used to create the concrete form of the weight matrix A:

$$A=\{a(c),k(c)\}_\gamma=\begin{cases} a(c)[\gamma],\gamma=1 \\ k(c)[\gamma],1<\gamma\leq\dfrac{JK+1}{2} \end{cases} \tag{8.5}$$

As a result, algorithm 1 provides a summary of the SDL filter learning procedure. The feature map or picture input I^N has to be divided up into many patches, which are then utilised to sweep feature matrices both horizontally and vertically.

Algorithm 8.1: the filtering process of SDL

1: Notation: The amount of extract patches, and N is the size of the training set.

2: Input: A graphic or feature map $\boldsymbol{I}^N$

3 : $\boldsymbol{Output}$: $\boldsymbol{Weight\ matrix\ A}$

4 : $\boldsymbol{for\ each\ layer\ l} := 1\ \boldsymbol{to\ numLayer\ do}$

5: $[\boldsymbol{p}]^N \leftarrow \boldsymbol{extractPatch}(\boldsymbol{I}^N, \boldsymbol{Patchsize})$

6: H&V Sweep: $\boldsymbol{Y} \overset{H}{\leftarrow} \boldsymbol{LSTM}\left(\boldsymbol{I}^N,[\boldsymbol{p}]^N\right), \boldsymbol{Y} \overset{V}{\leftarrow} \boldsymbol{LSTM}\left(\boldsymbol{Y},[\boldsymbol{p}]^N\right)$

7: ScatterNet: $\boldsymbol{o}^{(i)} = \sum_{\boldsymbol{C}=0}^{\boldsymbol{C}-1}(\boldsymbol{Y}^{(i)} * \boldsymbol{\varphi}_j + \left|\boldsymbol{Y}^{(i)} * \boldsymbol{\psi}_{j,\theta}\right|)$

8: A ← reshape(random(A))

9: for j := I to N do

10: $\boldsymbol{fmap}_j = \boldsymbol{O}^{(i)} * \boldsymbol{A}$

11: end for

12: $\boldsymbol{I}^N \leftarrow \boldsymbol{ReLu}(\boldsymbol{fmap})$

13: end for

C) Learning sparse features of filters

The common convolutional technique is equivalent to the learnable scattering transform according to Eq. (8.4). The differences are as follows: (1)

The input I has been changed to the result of a change by dispersion; (2) The convolutional layer's weight W has been changed This computation can be viewed as a 1 ×1 convolution, and it is applied to a learning matrix multiplicator A. Sparse transformations like the translation and scale transformation are included to cut down on the number of learning parameters and to improve this learning technique's suitability for small sample training settings.

The base-model (classifier) f using CNNs changes each parameter [W, b] by iteratively training on the dataset *D*, which is categorised using gradient descent as shown by Eq. 8.6:

$$\left\{\left[W',b'\right];f'\right\} \leftarrow \left\{\left[W,b\right];f\right\} - \alpha \nabla L_{cnn}\left(\left[W,b\right];f\right) \tag{8.6}$$

where α is the pace of learning, and $L_{cnn}(.)$ is the convolutional layer-based model training loss function. If entropy on the cross functional is employed to calculate the loss amount from the input value *x* and the real value *y*, it may be written as Eq. 8.7:

$$L_{cnn}\left(\left[W,b\right];f\right) = \frac{1}{|D|} 1|D| \sum_{(x,y)\ D} l\left(f\left(x;\left[W,b\right]\right),y\right). \tag{8.7}$$

Considering a using computer vision T, k = 3 for the kernel size, C for the channels, and [W, b] for learning, updating, along with the number of parameters [W′, b′] the following was calculated using CNNs: C ∗ 4 ∗ 3 ∗ 3 + 1 ∗ 4 ∗ 1 ∗ 1 = 36C + 4.

In this scenario, just the translation operator t's and the scale transformation operations s' parameters are taught employing the stochastic gradient descent technique; *A* and *b*'s values are fixed throughout the method of education. Assuming *f* is the basic classifier, the entire optimisation procedure considering the training loss $L_{tr}(.)$ can be expressed as Eq. 8.8:

$$\left\{\left[s',t'\right];f'\right\} \leftarrow \left\{\left[s,t\right];f\right\} - \gamma \nabla L_{tr}\left(\left[s,t\right];f\right). \tag{8.8}$$

As a result, it proceeds to calculate Eq. (4) using the suggested SDL, which is equivalent to eq. (9):

$$O^{(i)}\left(X,A,s',t'\right) = X * \left(s' \cdot A\right) + \left(b + t'\right) \tag{8.9}$$

where s′ ⊙ *A* stands for Multiplication of elements, When a module with Strip-Recurrent is used to perform the scattering transform, the outcome is *X*. The balanced matrix *A* is sized by *s*(1 × 1) and then shifted by t(1 × 1) in a filter with a 3 × 3 kernel. As a result, the number of components is: C * 4 * 1 * 1 + 1 * 4 * 1 * 1 = 4C + 4. Since only a column matrix, rather than

the entire weight matrix A, is learned, it is clear that sparse transitions s, t can efficiently reduce the training parameters.

Algorithm 8.2 summarises the methods used to learn sparse features in a computer vision problem T, that, using the aforementioned reasoning, is utilised to train a light-weight model to produce the ideal sparse weight matrix A.

Algorithm 8.2: Predicting violent individual's steps within a task T

1 : ***Input*** : ***Displaying task T*** , ***learning rate*** γ , ***base classifier f*** , ***sparse parameters for learning*** $[s,t]$, ***and feature X is*** $O^{(i)}$ ***of Algorithm***

2 : ***Output*** : ***Updated f' and*** $[s,t]$, ***Updated feature map*** $O(i)$

3 : ***for samples in T do***

4: ***Evaluate(loss function)*** $L_{tr}(.)$

5 : ***Optimize*** $[s,t]$ ***by Eq.*** (8.7)

6 : ***end for***

7 : ***while not done do***

8 : ***Update*** $O^{(i)}$ ***by Eq.*** (8.8)

9 : ***Compute ClassAcc for T***

10 : ***end while***

D) Learning the weight matrix a's initial value

The gradient descent convergence rate and model learning effectiveness will be impacted by learning the starting value of A for the common convolutional layer is comparable to initialising the weights. In order to lessen the negative effects of improper initialisation, batch normalisation is introduced to the suggested learnable scattering layer. However, this work finds that on some image classification datasets, this sometimes decreases classification accuracy. The following Eq. 8.10 is used to get the initial value of A. Because of its robustness and consideration of the rectifier nonlinearities, this method is an ideal one for weight initialisation:

$$A_{init} = Random(n_{in}, n_{out}) * \sqrt{\frac{2}{n_{in} * a}},$$

$$n_{in} = n_{out} = \left(7 * \left(\frac{C}{2}\right) \times F \times h \times h\right) \quad (8.10)$$

where α is the half-axis of ReLU's inverse slope, n_{in} is the size a weight matrix A, along with the output and input channels' respective sizes, C and F, and the kernel's size, h.

8.3.4 Hyper-parameter tuning using IPOA

8.3.4.1 POA

New meta-heuristic optimisation methodology called POA was inspired by pelican hunting techniques [24]. It involves simple computation. The world's warm waterways are home to pelicans, which mostly inhabit lakes, rivers, beaches, and wetlands. Pelicans typically live in groups and have excellent swimming and flying abilities. They mostly eat fish and have good observational abilities and keen eyesight when flying. Pelicans hunt by diving headfirst into the ocean after spotting their prey and flying at its feet from an altitude of 10 to 20 metres. Pelicans may fly in a line or a U shape while swooping down on fish in the water. The fish swims upward as a result of the bird's wings flapping the water, and the fish is then scooped up and placed in the neck pouch. This behaviour is displayed by pelicans when they come upon fish schools. The aforementioned description was used to develop the POA algorithm's mathematical model.

(1) **Initialisation:** The site of the i-th pelican in an space will be known if there are N pelicans there may be determined is $P_i = \left[p_{i1}, p_{i2}, \ldots, p_{im}, \ldots, p_{iM}\right]$, Equation (8.11) gives the following expression for the spot P within the N pelicans:

$$P = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2m} & \cdots & p_{2M} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{i1} & p_{i2} & \cdots & p_{im} & \cdots & p_{iM} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{Nm} & \cdots & p_{NM} \end{bmatrix}, i = 1,2,\ldots\ldots\ldots,N \quad (8.11)$$

where p_{im} identifies the m-th dimension. Equation 8.12 provides position updates for pelicans; they are originally arranged in a predetermined region at random.

$$P_{im} = low_m + random\left(up_m - low_m\right), i = 1,2\ldots,N; m = 1,2,\ldots M; \quad (8.12)$$

where low_m, up_m. Here, 'random' denotes a number selected uniformly at random from the interval [0, 1], and it signifies the pelican's search area.

(2) **Approaching the prey:** Here the pelican locates its meal and swoops down on it from great heights. Equation (8.13) explains how the pelican revises its position following each iteration, and the random distribution of the prey enhances the pelican's ability to traverse the search space.

$$P_{im}^{t+1} = \begin{cases} P_{im}^t + rand\ \left(S_m^t - \lambda\ P_{im}^t\right),\ F\left(P_S\right) < F\left(P_i\right) \\ P_{im}^t + rand\ \left(P_{im}^t - S_m^t\right), \qquad F\left(P_S\right) \geq F\left(P_i\right) \end{cases} \tag{8.13}$$

where t is the current iteration; P_{im}^t indicates where the i-th pelican is in relation to the m-th dimension; S_m^t is the location of in the m-th dimensions, the prey; λ is at random either 1 or 2; $F\left(P_S\right)$ is the value of the primary purpose; $F\left(P_i\right)$ indicates the i-th pelican's fitness function value in the m-th dimension.

(3) **On the water's surface, wings:** Pelicans stretch their wings once they are at the fish by using the surface of the water to lift them up, after which they scoop them up in their throats pouches. Equation 8.14 simulates this pelican hunting habit analytically.

$$P_{im}^{t+1} = P_{im}^t + \gamma \cdot \left(\frac{T-t}{T}\right) \cdot \left(2 \cdot random - 1\right) \cdot P_{im}^t \tag{8.14}$$

where t indicates how many iterations there have been performed as of the moment and T represents the greatest sum of repetitions; $\gamma \cdot \left(\frac{T-t}{T}\right)$ is the proximity radius of P_{im}^t, and in order to find a better solution, it displays the size of the local search area for population members. The extent of the residents' locality is represented by the random value, which ranges from 0 to 1.

8.3.4.2 IPOA

The efficiency of the optimisation process could be further increased after making changes to the original POA algorithm. The following is the precise improvement strategy.

(1) **Initialisation strategy:** An introduction to the tent chaotic mapping follows; the pelicans must be initialised, the original POA's method of random generation is replaced and Eq. 8.12 may be recast as follows (Eq. 8.15– 8.16):

$$p_{im} = low_m + Tent \cdot \left(up_m - low_m\right), i = 1, 2, \ldots, N; m = 1, 2, \ldots, M; \tag{8.15}$$

$$Tent^{t+1} = \begin{cases} \dfrac{Tent^t}{z}, Tent^t \varepsilon \left[0, z\right) \\ \dfrac{\left(1 - Tent^t\right)}{\left(1 - z\right)}, Tent^t \varepsilon \left[z, 1\right] \end{cases} \tag{8.16}$$

where T characterises the higher amount of iterations and with t iteration count; where $z \in (0,1), Tent^t \in [0,1$, $t = 1, 2, \ldots, T$.

The POA algorithm's global search performance is now enhanced by initialising the pelicans' positions using the tent chaotic map.

(2) **Moving toward prey:** At this point, the pelican may continuously update its position because the dynamic weight factor [25] drops adaptively toward the conclusion of this edition; the pelican is able to speed up convergence while doing a better local search. When the pelican can conduct a more effective in the beginning of the iteration, a global search that provides a significant value. Equation 8.17 allows Eq. 8.13 to be reformulated as follows:

$$P_{im}^{t+1} = \begin{cases} \theta = \dfrac{e^{2\left(\frac{1-t}{T}\right)} - e^{-2\left(\frac{1-t}{T}\right)}}{e^{2\left(\frac{1-t}{T}\right)} + e^{-2\left(\frac{1-t}{T}\right)}} \\ P_{im}^t + rand\ \left(S_m^t - P_{im}^t\right)\ \theta, \quad F\left(P_S\right) < F\left(P_i\right) \\ P_{im}^t + rand\ \left(S_m^t - P_{im}^t\right)\ \theta, \quad F\left(P_S\right) x \geq F\left(P_i\right) \end{cases} \tag{8.17}$$

Table 8.1 gives the parameter setting of IPOA.

8.4 RESULTS AND DISCUSSION

8.4.1 Experimental setup

The ASIIR Dataset, which includes human actions including kicking, striking, and punching, was used for the studies. The tests were run using Python 3.5 Keras on a workstation equipped with an NVIDIA GeForce GTX 1080.

Table 8.1 Parameter setting

Algorithm	*Parameter Setting*
IPOA	$\lambda = \theta$ $\gamma = 0.2$

8.4.2 Performance metrics

Accuracy, recall, precision, and F1 are common measurements as shown in Eq. 8.18– 8.21:

- True positives (TP): the total sum of incidents that were rated positively;
- True negatives (TN): the overall sum of occurrences that were labelled as being negative;
- False positives (FP): the quantity of negative events that were labelled as positive;
- False negatives (FN): how many good occurrences were labelled as negative;

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{8.18}$$

$$Precision = \frac{TP}{TP + FP} \tag{8.19}$$

$$Recall = \frac{TP}{TP + FP} \tag{8.20}$$

$$F1 = \frac{Precision * Recall}{Precision + Recall} \tag{8.21}$$

Table 8.2 and Figures 8.8–8.12 show that the R-CNN achieves 86.6% of Accuracy, 83.7% of Precision, 87.6% of Recall, 87.8% of F1. YOLO-v2 achieves 88.6% of Accuracy, 85.2% of Precision, 89.5% of Recall, 89.5% of F1. SSD achieves 93.9% of Accuracy, 92.2% of Precision, 94.6% of Recall, 95.2% of F1. Proposed SDL model achieves 97.8% of Accuracy, 97.7% of Precision, 96.26% of Recall, and 97.3% of F1.

In the analysis of Table 8.3 and Figures 8.8–8.12, R-CNN achieves 81.02% of Accuracy, 63.7% of Precision, 70.4% of Recall, 67.8% of F1. YOLO-v2 achieves 82.54% of Accuracy, 55.2% of Precision, 82.6% of Recall, 79.5% of F1. SSD achieves 85.38% of Accuracy, 83.2% of Precision,

Table 8.2 Classification without IPOA

Models	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1 (%)*
R-CNN	81.02	63.7	70.4	67.8
YOLO-v2	82.54	55.2	82.6	79.5
SSD	85.38	83.2	87.6	86.2
Proposed SDL model	92.10	92.7	91.26	90.3

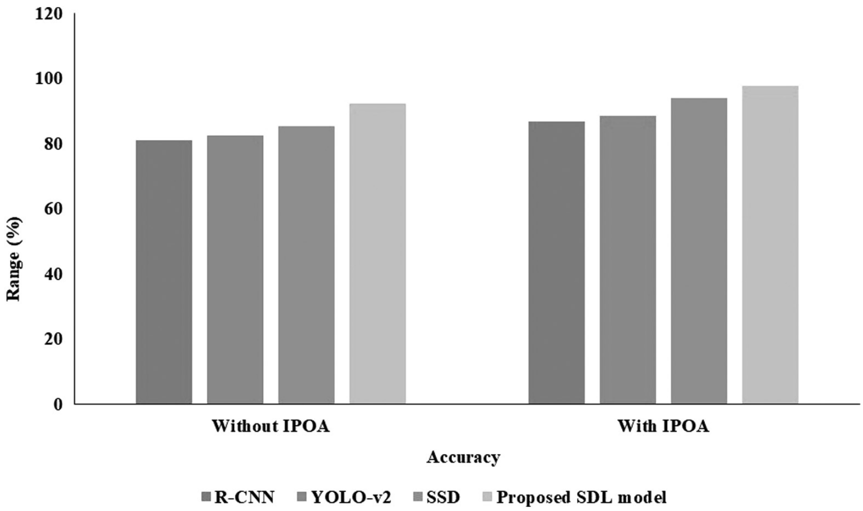

Figure 8.8 Accuracy

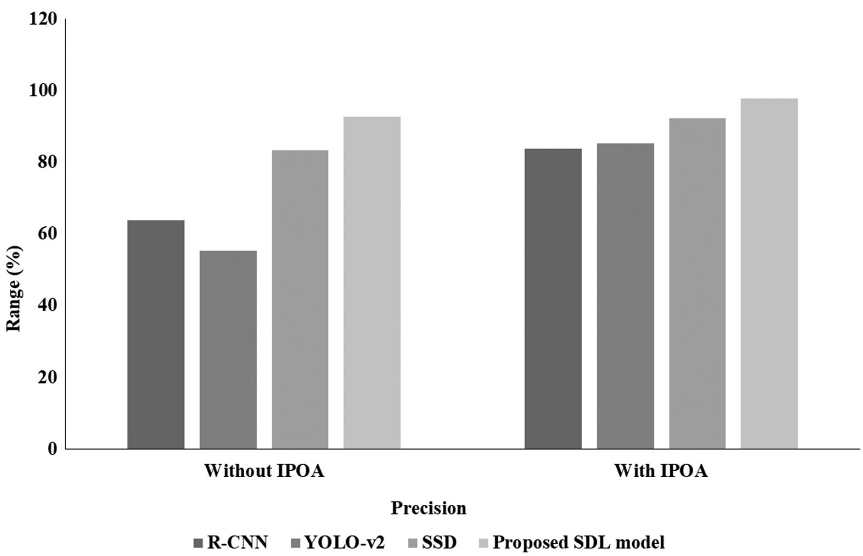

Figure 8.9 Precision analysis

87.6% of Recall, 86.2% of F1. Proposed SDL model achieves 92.10% of Accuracy, 92.7% of Precision, 91.26% of Recall, 90.3% of F1. Due to the hyper-parameter tuning using IPOA, this paper achieves higher results than other existing models.

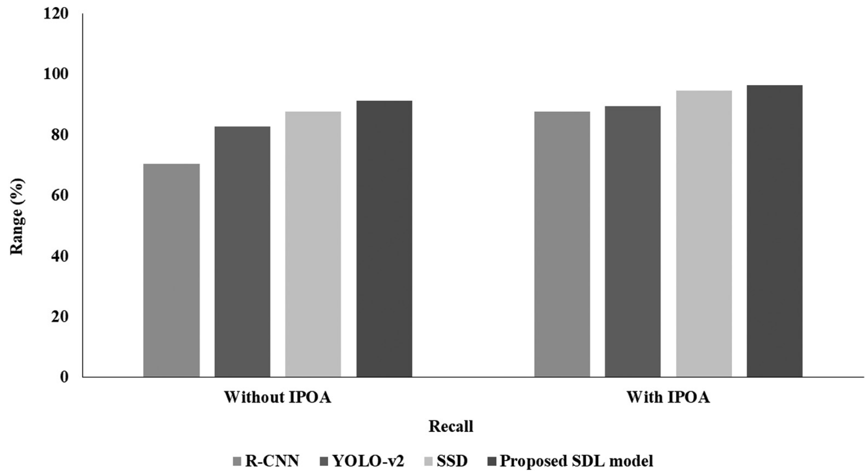

Figure 8.10 Recall evaluation

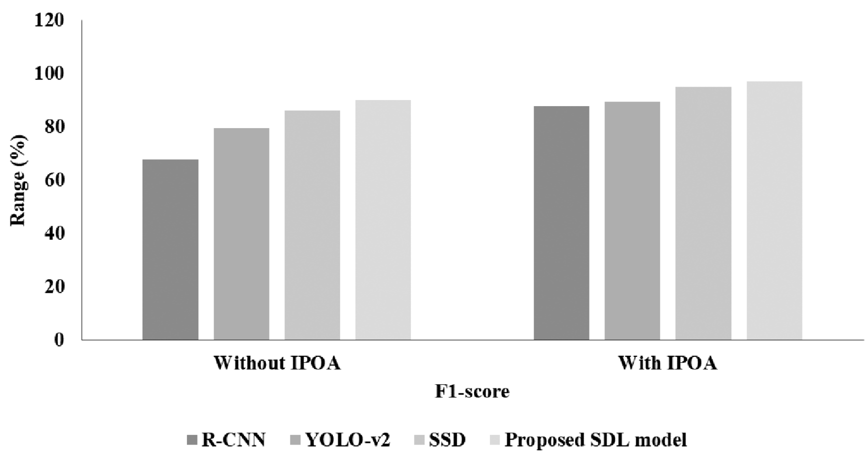

Figure 8.11 F1-score analysis

Table 8.3 Classification with IPOA

Models	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1 (%)*
R-CNN	86.6	83.7	87.6	87.8
YOLO-v2	88.6	85.2	89.5	89.5
SSD	93.9	92.2	94.6	95.2
Proposed SDL model	97.8	97.7	96.26	97.3

8.5 CONCLUSION

The study created an SDL model for predicting violent entities using a real-time drone surveillance scheme framework for identifying one or more individuals engaging in violent behaviour from aerial photographs and the drone's frame of view, and then re-identifying them once more in successive frames. A multi-timescale framework was created in this study to account for anomalous human activity happening at many timeframes. To find unusual human behaviour, we employ the multi-timescale forecasts. The suggested SDL network accelerates training with comparatively less labelled examples by using ScatterNet features with structural prior initialisation. Since gathering annotated examples is costly, this application benefits from using fewer marked cases. The publication also presented the ASIIR dataset, which helps other academics who want to employ deep learning methods in applications that involve aerial surveillance. IPOA optimisation is employed in this work for hyper-parameter adjustment. The suggested strategy outperforms cutting-edge methods on the dataset. This study's accuracy rate of 97.8% is higher than that of other models currently in use. The framework, in our opinion, would be helpful in identifying aggressive people in public places or at huge gatherings. This study project will eventually include collective aberrant actions that fit our definition. Additionally, a lot of motion characteristics are introduced to incorporate Alliteration accuracy is improved by incorporating strong graphic elements into the frame.

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Chapter 9

An optimal framework for intelligent machine learning-based early diagnosis of pre-diabetes and type 2 diabetes using genomic data

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LIST OF NOTATIONS

Mu: Expression of gene
z: Data
Mu(z): Gene expression data
R: Preprocessing parameter
Sl,tl: Noise features
N: Feature evaluation variable
n_{max}: Maximum matching features
n_{min}: Minimum matching features
B: Class
(0,1): Illness class features
if(Mu[0,1]): Assessing the situation during testing
0: Normal features
1: Abnormal features
ts: Illness samples
M: Gene expression
u: Data
M(u): Gene expression data
n_b: Nan characteristics
y: Tracking parameter
S: Feature selection process parameter
b: Tracking parameter
S_f: Desired features
if(Mu[0,1]): Condition in the classification process
[0, 1]: Categorization function
1: Probability score
tk: Illness samples
CbMM: Coati-based multilayer model
CbFLNA: Chimp-based functional link neural approach
ML: Machine learning

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9.1 INTRODUCTION

Diabetes refers to a metabolic disorder characterized by elevated blood sugar levels. There is no long-term treatment for diabetes in the present world [1]. To enhance patient lifespan, early detection is required. As a result, early prediction needs a wide range of techniques and information sources [2]. To obtain compensation for this illness, strict monitoring is required to treat diabetes by medication and injection of insulin, routine exercise as well as diet, blood glucose monitoring, and regular consultation with doctors to assist in sustaining the state of diabetes [3]. It is one of the common disorders that might raise blood sugar or glucose levels. In daily life, the level of glucose often changes. Therefore, each patient requires careful eye inspection. Due to its inadequate relation to insulin, glucose takes up much space in blood cells [4]. Inadequate medication can cause high glucose levels. People may perish from the complications of diabetes worldwide [5]. People with diabetes can easily manage their health status to reduce danger. The risk of this severe disease is therefore decreased with regular monitoring. Early detection of diabetes is extremely difficult; hence, certain criteria, including predicting, quantitative, and systematic methods, are used [6]. The ability to combat this disease can be increased with the help of insulin and a nutritious diet. Diabetes can contribute to several illnesses, including heart illness, infection of the lungs, strokes, and a wide range of other illnesses [7]. The healthcare centers contain a sizable number of diabetic patients in their database. Different diabetes situations can be categorized [8].

Low insulin synthesis in blood cells can impact the immune system and decrease pancreatic activity throughout the body [9]. Diabetes causes metabolic illness because the insulin tolerance is lowered. The amounts of glucose in the blood are regulated by insulin. Diabetes is typically described as a form of cardiovascular illness [10]. The global fatality rate of diabetes has climbed by 70% during the past ten years. Early diabetes detection through machine learning (ML) is essential [11]. The Ml-based systems used in the medical evaluation system created to identify the beginning stages of diabetes signs, research in laboratories, and keeping track of all the data about the condition are highly beneficial in preventing people with diabetes from doing dangerous actions [12]. Presently, researchers concentrate on various database categories to foretell diabetes signs. The suggested approach is required to forecast the illness's beginning stages and routinely monitor blood sugar levels [13]. This strategy guarantees a healthy way of life necessary for survival on this planet. A gene shortage among the 40 genes that make up this condition results in genetic diabetes [14]. ML-based frameworks are a highly computing technique to enhance the accuracy of the beginning stages of prediction [15]. These days, kids are also affected by this illness. These genetic illness issues are influenced by several circumstances, including smoking, poor eating habits, excess body weight, and hereditary predispositions [16].

Extremely accurate illness identification allows persons with the following disorders to postpone disease development and enjoy better overall health [17]. Artificial intelligence techniques are classified into two types [18]: forecasting future illnesses and diagnosing anomalies [19]. The beginning of diabetes may be predicted using advanced forecasting techniques based on present and past health conditions [20]. The illness is influenced by inherited issues, which can lead to a variety of issues as well as increase the risk of premature death [21]. On a limited basis, initial potential gene and association analysis has found a variety of disease-related features [22]. No matter where a variety of genetics were localized, those genetic examinations were found to be completely unsuccessful [23]. Widest association techniques based on genomes have lately aided in identifying genes connected to type 2 diabetic diseases [24]. Furthermore, the genomic data contains single-molecule polymorphisms [25], which have been shown to characterize numerous disorders and are common in the genomes of humans within a collection of species [26].

In the beginning stages of evaluation, intelligence-based ML approaches provided a framework to learn and obtain additional intelligence-based experience [27]. Analyzing the framework involves evaluating the algorithm's input data [28]. As a result, it is beneficial to base decision-making controls and precise predictions on the beginning stages of diagnosis [29]. After data preparation, the data will be preprocessed, the linked illness will be fixed, and unneeded information will be removed from the database [30]. Assume that the large amount of learning data makes decision-making tough. The designed method generates several logic processes, such as probability evaluation and statistics assessment [31]. The framework must examine the information and learn from experience. The optimization is then carried out using the fresh dataset after evaluating the accuracy of the efficiency assessment [32]. The algorithm assists in tracking, segmenting, and categorizing the illness before determining its level of seriousness. The created model depends on the ML method for comprehending the behavior and understanding of diabetics, and the effectiveness is assessed. Therefore, the current study aimed to construct the most effective neural network as the diabetes diagnosis approach. The benefits of neural network in diabetes diagnosis approach includes,

- High accuracy in noisy diabetes data.
- Strong generalization to new patients.
- Robust to data noise and incompleteness.
- Improved interpretability for healthcare.
- Efficient, scalable, and real-time deployment.

9.2 PROPOSED CBMM MODEL

Diabetes prediction is a critical area of medical research, and diabetes prediction is a matter of paramount importance. Existing models, however,

frequently need to work on data quality challenges, particularly the presence of noisy genomic features, which complicate the quest for precise predictions and optimal performance. In response to these hurdles, this study introduces two innovative approaches: the Coati-based multilayer model (CbMM) and the chimp-based functional link neural approach (CbFLNA), tailored to enhance diabetes prediction accuracy. These methods adhere to a systematic framework, encompassing essential stages such as data preprocessing, feature selection, classification, and gene expression analysis. The process commences with the assimilation of data, which undergoes rigorous preprocessing and feature selection to unveil meaningful insights within the genomic data despite potential noise and Nan features. Subsequently, these models step in to forecast and categorize health conditions.

9.2.1 PROPOSED CBMM MODEL FOR DIABETES PREDICTION

A new Coati-based Multilayer model (CbMM) is developed for this genomic feature evaluation. In this section, the early forecast was carried out based on the unique human genetic alterations. Therefore, the probability of developing diabetes was anticipated more precisely based on the genetic characteristic alteration. Finally, in terms of f-score, Accuracy, Precision, Error Rate, and Recall, the predicted robustness was evaluated and contrasted to other latest related works. The suggested process is depicted in Figure 9.1.

The design of the suggested methodology is depicted in Figure 9.1. The goal of this research is to use genetic information to predict diabetes earlier. The performance enhancement in identifying genes in each database is compared in this research.

Process of the proposed CbMM model: The intended methodology includes five processing layers: input, hidden, classification, optimization, and output. The technique can also be carried out utilizing the multilayer perceptron as well as the coati optimization function. In an artificial neural system, the multilayer perceptron is an element. The best results in terms of filtering are provided by the deep, intelligence multilayer perceptron framework. In this case, the hidden layer of the CbMM is used to carry out the filtering.

The CbMM methodology's process layers are described in Figure 9.2. Here, the collected dataset was loaded into the input layer, and the noise filtering was then carried out by the hidden layer. The classification layer can ingest the data that has been noise-filtered. The coati optimization function is then used to adjust the categorized parameters, whereas the output layer contains the optimized outcome.

Data Training and Preprocessing: The genetic data was collected and imported at the initial step. The data training process can be described by the Eq. 9.1.

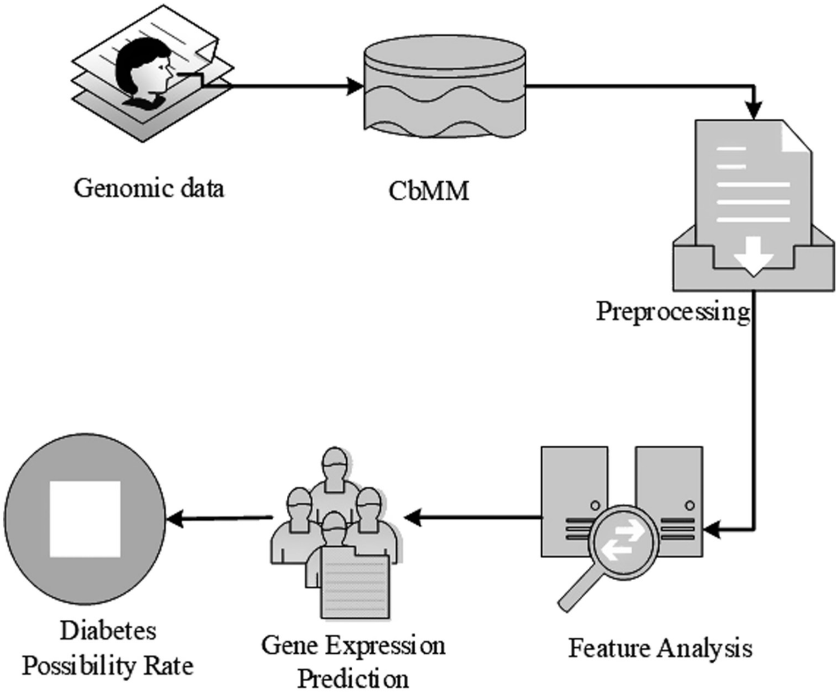

Figure 9.1 Proposed architecture of CbMM

$$H\left(Mu(z)\right) = Mu(z)\{1,2,3,......K\} \tag{9.1}$$

whereMu is termed as the expression of gene, data was indicated as$z$and $Mu(z)$ is displayed as gene expression data. The preprocessing or noise filtering step in the machine learning approach has reduced the level of difficulty of the algorithm used to execute the validation and training functions. Preprocessing, then, evidently plays a major part in the workflow.

$$R\left(Mu(z)\right) = sl - (z)\left[(sl,tl)\right] \tag{9.2}$$

Machine learning methods are completely relying on data. It is an extremely significant aspect that enabled the training of models. The dataset was gathered and comprises both typical and several noise features. Preprocessing is therefore required to remove all noise features and provide an unaltered dataset. Preprocessing is performed by the Eq. 2.2. In this the preprocessing parameter is$R$. The noise features are indicated as sl,tl and can be termed as normal features. The dataset without noise feature is the outcome of the preprocessing stage.

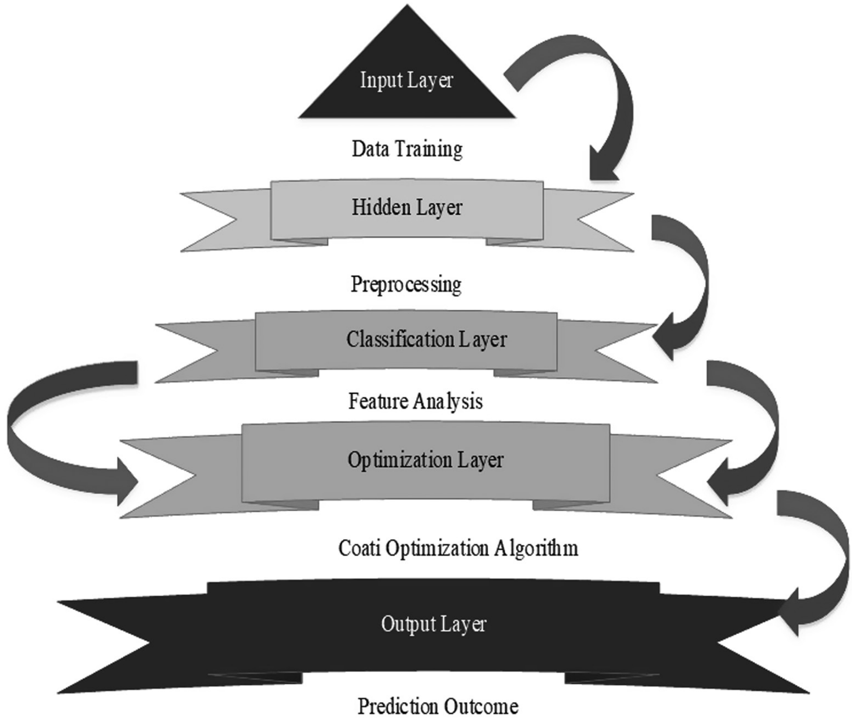

Figure 9.2 Processing layers of CbMM

Feature Analysis: The feature evaluation method has been used to lower computing costs. All trained datasets are evaluated in feature analysis and the most identical illness features are extracted. With the highest possible accuracy score, the gene expression in the specific test data has been anticipated and assessed. Both the greatest and least matching features are present in the dataset.

$$N\left(Mu\left(z\right)\right) = n_{\min} + B\left(0,1\right) * \left(n_{\min} - n_{\min}\right) \tag{9.3}$$

The feature evaluation variable is indicated as N.The present maximum matching features are indicated as $n_{\min}$ and the minimum matching features are indicated as$n_{\min}$. Therefore the illness can be distinguished from its maximum matched features by removing the minimum matched features. Hence the maximum matched features are extracted. The class is represented as $B$and the illness class features can be denoted as$\left(0,1\right)$. The mathematical formulation for feature evaluation can be indicated in Eq. 9.3.

Classification and Prediction: The normal data and illness features must be determined using a classification framework. The initial dataset often

includes both abnormal and normal features. Determine the gene expressions that categorized the illness's features using the illness data. Finally, the classification layer was utilized for categorizing the illness features.

$$P\left(I_f\right)=\begin{Bmatrix} if\left(Mu=0\right) & Normal \\ else & Abnormal \end{Bmatrix} \tag{9.4}$$

Where, the variables of the illness were established in the format of (0, 1). Assessing the situation during testing may occur as$if\left(Mu\left[0,1\right]\right)$. The categorization of the illness features are illustrated in Eq. 2.4. In this 0 denotes the normal features, and 1 denotes the abnormal features.

Gene Expression Analysis: After finishing the intention of feature evaluation and classification step, anticipate the validated illness specimens in the present gene features. Prediction of gene expression can be calculated by utilizing the Eq. 9.5.

$$Ge_p = 1 \times \frac{ts}{g_{\max}} + 0.1 \tag{9.5}$$

Where, 1 indicates the possibility score corresponding to the highest number of present genes that can be examined. Additionally, 1 was the probability denoting 100% of the validated samples of the current gene. The illness samples that were validated are noted as, ts as well as $g_{\max}$have included certain essential components, such as protein, carbohydrate, and blood cholesterol rates. These properties of the genes vary according to the genomic dataset.

Algorithm: 9.1 CbMM

Start

{

Initialization dataset()

{

$\text{int}\, Mu(z) = 1,2,3....K;$

//initialize the dataset

}

Preprocessing()

{

$\text{int } R, sl, tl;$

//initialize the preprocessing parameters

$R(Mu(z)) \longrightarrow \text{Re}\, move - sl(Mu(z))$

//Eliminating the noise features

}

```
Feature analysis()
{
    int n_min, n_max, N;
    //initialize the feature extracting parameters
    Extract ⟶ n_max(Mu(z))
    //extracting the maximum matching features
}
Classification and prediction()
{
    if(Mu(z) = 0)
    {
    Normal
    }else Abnormal
Gene expression()
{
    Ge_p ⟶ Classification(g_max)
    //classified the maximum number of genes
}
}
Stop
```

The advanced methodology's progressive processes are depicted in Figure 9.3. The algorithm 9.1 represents the developed pseudo code of the complex formulation of mathematics. The performance of the innovative CbMM was commended throughout the required preprocessing steps.

9.2.2 Proposed CbFLNA model

A new chimp-based functional link neural approach (CbFLNA) is being developed to examine and detect type 2 diabetes and pre-diabetes. Furthermore, genetic information is being used in this research to estimate pre-diabetes as well as type 2 diabetes. Pre-diabetes and type 2 diabetes are predicted according to insulin and blood pressure levels. The genetic information was preprocessed and sent into the classification layer after the feature evaluation, diabetes estimation, and classifications were done. Lastly, the parameters of performance were evaluated and contrasted to other systems.

The framework of the suggested methodology is depicted in Figure 9.4. The goal of this research is to analyze and detect type 2 diabetes as well as pre-diabetes. The contrasting analyses provide the performance evaluation in gene detection in every database.

Process of the proposed CbFLNA model: The suggested approach comprises five layers: an input layer, a filtering layer, a classification layer, an

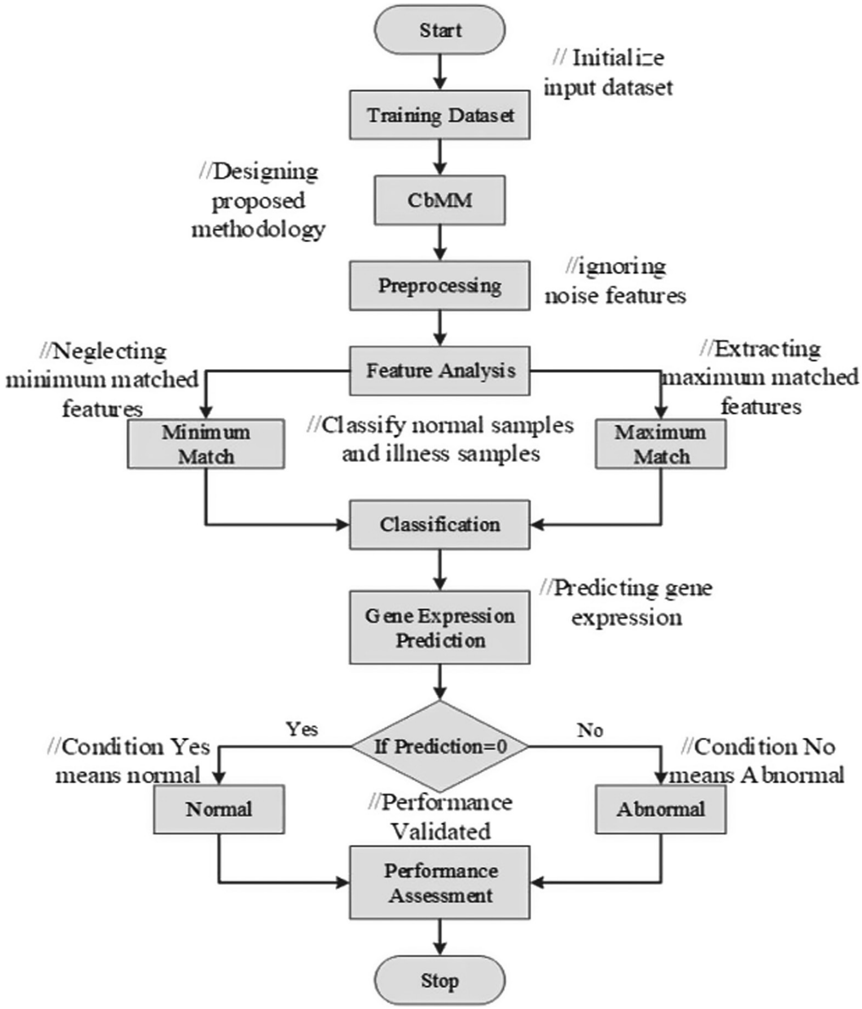

Figure 9.3 Flow diagram of CbMM

optimization layer, and an output layer. The chimp-based functional link neural approach (CbFLNA) can be used to complete the procedure.

The functional layers of the new CbFLNA are depicted in Figure 9.5. The data gathered was loaded into the input layer in this instance. The filtering layer has performed the preprocessing. The data without noise was gathered and fed into the classification layer. The variables are then categorized and implemented utilizing the chimp optimization algorithm, with the optimal outcome provided in the output layer.

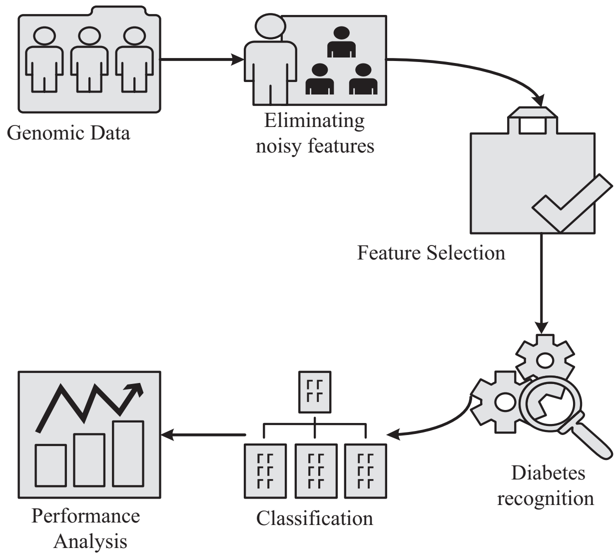

Figure 9.4 Proposed architecture of CbFLNA

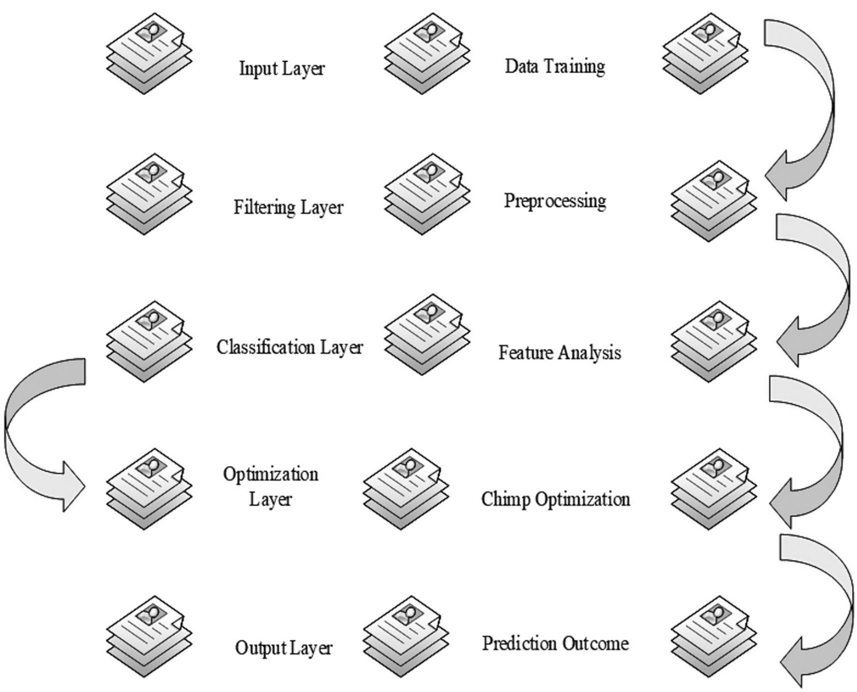

Figure 9.5 Processing layer of CbFLNA

Preprocessing: Initially, genomic information had been gathered and loaded into the Python platform. The function of data training is defined in Eq. 9.6.

$$M(u_n) = (u_1, u_2, \ldots\ldots u_c) \tag{9.6}$$

where M represents gene expression, data is given as u, and $M(u)$ represents gene expression data, as well as c is the number of data. The data reliability is high, which influences the estimated outcome, and it has lowered the level of difficulty of the algorithm. As a result, data preprocessing is an essential step in the process.

$$R(u_n) = y(u_n - u_b) \tag{9.7}$$

The input database comprises both normal as well as Nan characteristics. The preprocessing method is utilized to remove Nan features and normalize the dataset, resulting in an apparent dataset. The preprocessing process is performed utilizing Eq. 9.7, where R is the preprocessing parameter. Both Nan characteristics are represented asn_b, and y are the tracking parameter. The apparent dataset is the end result of the preprocessing algorithm.

Feature selection: The feature choosing process determines the subset of the most important characteristics in the dataset. It shortens executing time while increasing prediction accuracy. The technique of choosing and extracting the most closely matched illness features from a dataset is referred to the feature selection. The dataset includes the illness's maximum and minimum matched attributes.

$$S = M(u_n) + b[u_n - s_f] \tag{9.8}$$

The process of choosing features was carried out by Eq. 9.8, where S is the parameter of the feature selection process. The dataset comprises both desired and undesirable properties. The process of choosing features is completed in order to obtain the desired features. The tracking parameter is indicated as$b$, while the desired features are denoted as S_f.

Classification and prediction: The categorization process is utilized to identify illness characteristics as well as normal data. Typically, the first dataset includes both normal and abnormal features. As a result, the illness feature dataset was used to discover gene expression and classify the illness's features. Finally, in the classification layer, the illness features were classified.

$$D(I_f) = \begin{Bmatrix} if\,(M = 0) & Normal \\ else & Abnormal \end{Bmatrix} \tag{9.9}$$

The condition in the classification process is expressed as $if\left(M[0,1]\right)$. Equation 9.9 reflected the categorization process of illness characteristics. In two situations [0, 1], the categorization function was used. Where 0 denotes normal features and 1 denotes abnormal features.

Disease prediction: After the feature choosing and classification process, the prediction of the evaluated illness samples using the current gene features. Detecting illnesses is achieved by the Eq. 9.10.

$$\Pr = 1 \times \frac{tk}{G_{\max}} + 0.1 \tag{9.10}$$

Where, the probability score is indicated as 1, and the maximum latest genes have been examined. More than 1 is the probability that the examined samples of the current gene are 100% accurate. The illness samples that were analyzed can be visualized astk. $G_{\max}$ comprises certain significant characteristics like blood pressure, blood sugar, blood protein, as well as blood cholesterol levels. According to a trained genomic illness database, these gene characteristics have been altered.

Algorithm 9.2: CbFLNA

```
Start
{
   Data initialization()
   {
    int M(u_n) = 1,2,3,....n;
    // initialize illness database
      }
      Pre-processing()
      {
           int R, y, n_b;
        // initialize pre-processing parameters
          R(u_n) ⟶ u_n − n_b
        // Removing noise features
      }
      Feature selection()
      {
         int S, s_f;
         // initialize feature selection parameters
         Select ⟶ u_n − s_f
         //selecting maximum matching features
      }
```

```
Classification()
  {
   if(M(u)) = 0
   {
      Normal
    }else (Abnormal)
    }
    Gene expression()
    {
         Pr ⟶ Classification(G_max)

         // classified the maximum genes
  }
}
Stop
```

The sequential process for implementing the proposed framework is depicted in Figure 9.6. The complicated mathematical formulation's pseudo code is then presented in the algorithm 9.2. The dataset includes both normal and abnormal features. The illness samples were categorized during the initial step of feature selection. Furthermore, gene expression was exclusively found in illness samples. Following the completion of the outlined processes, the efficiency of the CbFLNA was evaluated using several classification criteria.

9.2.3 Result

CbMM Model: The innovative CbMM methodology is implemented using the Python programming language and the Windows 10 operating system. Data was initially gathered, and the system was trained. Both abnormal and normal data features are present in the data.

The specification of the execution variables is represented in Table 9.1. The noise features were eliminated during the preprocessing stage, and the features without error were loaded into the classification stage. The classification step also assessed performance and anticipated gene expression.

Case study of CbMM Model: *Specific test validation was performed to evaluate the performance of the suggested approach, and the findings are reported progressively. The genomic dataset was used for the validation of tests. Demographic as well as medical information are included. There are 15485 samples in the dataset as a whole. 12388 of the total samples are used for training, while 3097 are used for testing.*

Details about the database are described in Table 9.2. Additionally, samples are taken into account for training, with 6209 normal samples and 6179 abnormal samples. Additionally, 3097 samples are considered for testing, of which 1519 are normal and 1578 are abnormal.

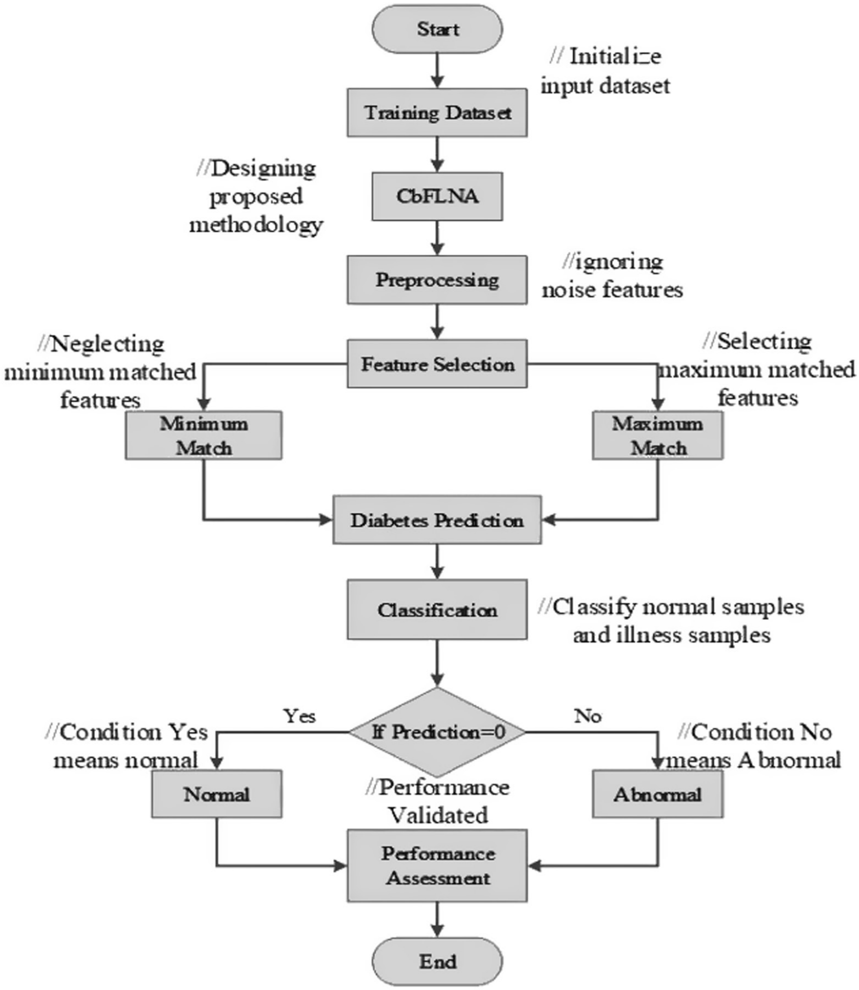

Figure 9.6 Flow diagram of CbFLNA

Table 9.1 Execution parameters specification

Description of parameters	
Programming environment	*Python*
Database	Genomic data
Dataset format	Numerical data
Operating system	Windows 10
Deep Network	Multilayer network
Optimization	Coati optimization

Table 9.2 Database details

Total samples: 15485	
Normal	7728
Abnormal	7757
Training(80%):12388	
Normal	6209
Abnormal	6179
Testing(20%): 3097	
Normal	1519
Abnormal	1578

The CbMM's accuracy and loss evaluation for the training epoch is shown in Figure 9.7. The testing and training validation precision score is used to assess the accuracy of the diabetic forecasting system. The failure probability of the developed framework is calculated using loss measures, which are evaluated during concurrent training and testing validation stages.

The anticipated outcome was revealed as a confusion matrix in Figure 9.8. Positive and negative ratings for each true and false division represented the categorization result. The forecast, in this instance, was divided into two distinct samples, 0 and 1. The normal value is 0, and the abnormal value is 1.

Performance of CbMM Model: The proposed CbMM model scored higher on all metrics, such as accuracy, precision, recall, and f-score, than any other model. The designed novel CbMM's overall performance has also been recorded in Table 9.3.

The recognition efficiency for all prediction metrics was 99.70%. The accuracy score for the suggested method was 99.70%. In comparison to the current approach, the accuracy rate is high. The innovative CbMM performed exceptionally well, obtaining the best outcome in the diabetes forecasting parameters.

CbFLNA model: The novel CbFLNA methodology has been tested and executed in the Windows 10 system using Python. The genetic data dataset is being examined for testing validation. The data set comprises both normal and abnormal information.

The execution variables are specified in Table 9.4. Initially, training faults were eliminated during the preprocessing step. The data without error was then fed into the classification step. Furthermore, gene expression was predicted, and efficiency can be assessed using a variety of metrics.

Case study of CbFLNA Model: Some test evaluations were carried out to examine the functional efficiency of the suggested approach, and outcomes were documented in an organized manner. The diabetes as well as gene datasets were used for test validation. It has a total of 1701 samples. There are 1360 training samples and 341 testing samples among the total samples.

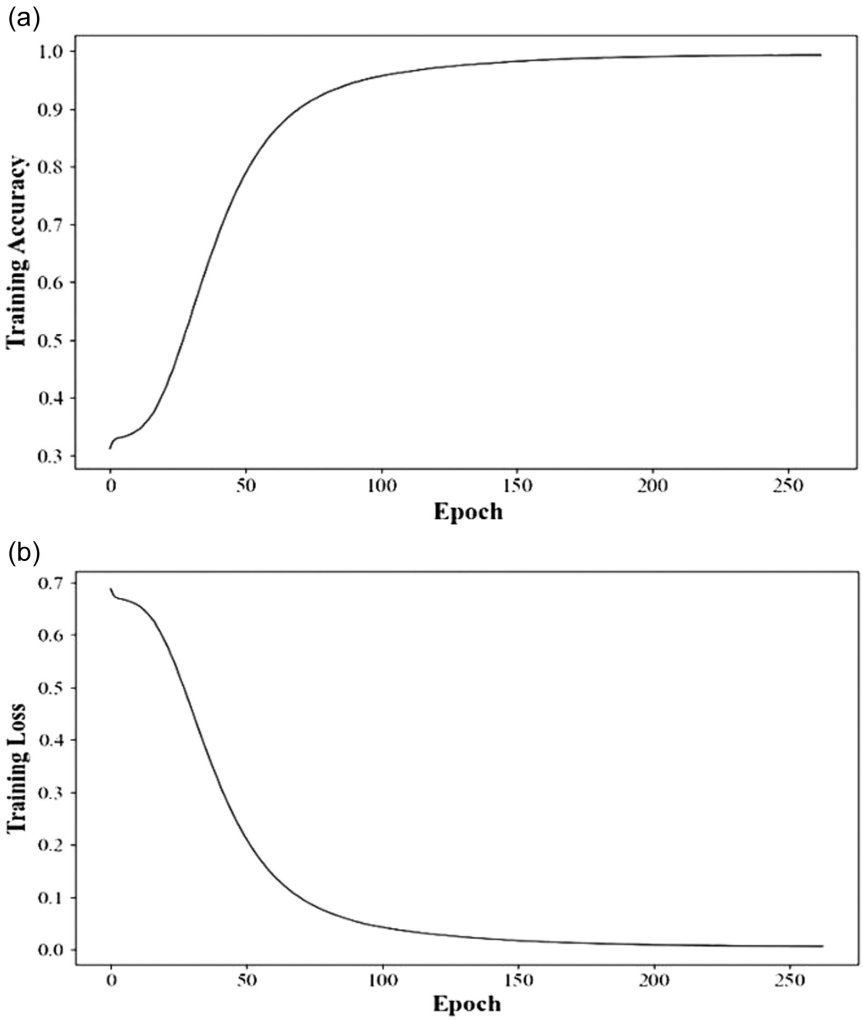

Figure 9.7 a) Training accuracy b) Training loss

The database properties are described in Table 2.5. Furthermore, samples have been selected for training, with 884 being normal and 476 aberrant. Moreover, the number of samples evaluated for testing is 341, with 234 being normal samples and 107 aberrant samples.

The accuracy and loss evaluation of the CbFLNA throughout the training epoch is depicted in Figure 9.9. The train and test validation accuracy scores are used to measure the system's reliability. The failure ratio of the developed approach is determined using loss metrics and measured during the dual training and test validation processes.

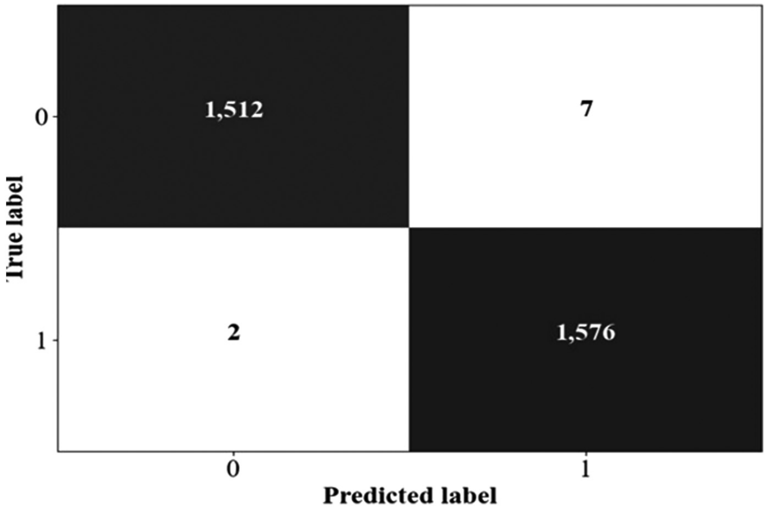

Figure 9.8 Confusion matrix

Table 9.3 Performance of CbMM

Performance of CbMM	
Efficiency parameters	*Performance (%)*
Accuracy	99.70
Precision	99.70
Recall	99.70
f-score	99.70
Error rate	0.0029
Time	21.9302s

Table 9.4 Specification of Execution parameters

Description of parameters	
Programming environment	*Python*
Database	Genomic data
Operating system	Windows 10
Total sample count	1512
Deep network	Functional link neural network
Optimization	Chimp optimization

Table 9.5 Database details

Total no of samples: 1701	
Normal	1118
Abnormal	583
Training(80%):1360	
Normal	884
Abnormal	476
Testing(20%): 341	
Normal	234
Abnormal	107

In Figure 9.10, the projected outcome was revealed as a confusion matrix. Positive and negative scores for true and false classes were obtained as the categorization outcome. The forecast was divided into two categories: 0 and 1. The normal value is 0, and the abnormal value is 1.

Performance of CbFLNA Model: The novel CbFLNA achieved a highly accurate score from all performance analyses, supporting the suggested model's successful operation. It has been confirmed that the proposed methodology is ideally suited for type 2 diabetes prediction. The entire performance of the novel CbFLNA approach is depicted in Figure 9.11.

The recognition efficiency for all forecasting parameters was 99.70%. The accuracy of the suggested approach was 99.70%. In contrast to the current process, the accuracy rate is high. The proposed model achieved the best outcomes for the prediction parameters, demonstrating the novel CbFLNA's outstanding performance.

9.3 CONCLUSION

This chapter introduced two novel methodologies, the CbMM and CbFLNA, for diabetes prediction based on genomic data, focusing on patients' well-being. The genomic dataset containing medical and demographic information was employed to validate these approaches. The initial steps involved data preprocessing, eliminating noisy features and ensuring only relevant attributes were retained in the feature selection phase. The resulting error-free data served as input to the classification layer. We harnessed the Coati and Chimp optimization algorithms for feature selection for the CbMM and CbFLNA methodologies. The multilayer perceptron and exactness score were then used for diabetes prediction, categorizing the results into normal and abnormal classes. These efforts resulted in a diabetes prediction system with a remarkable accuracy rate of 99.70%, showcasing a 1% improvement compared to conventional models. Moreover, the error rate of the proposed methods was impressively low, at 0.0029% for

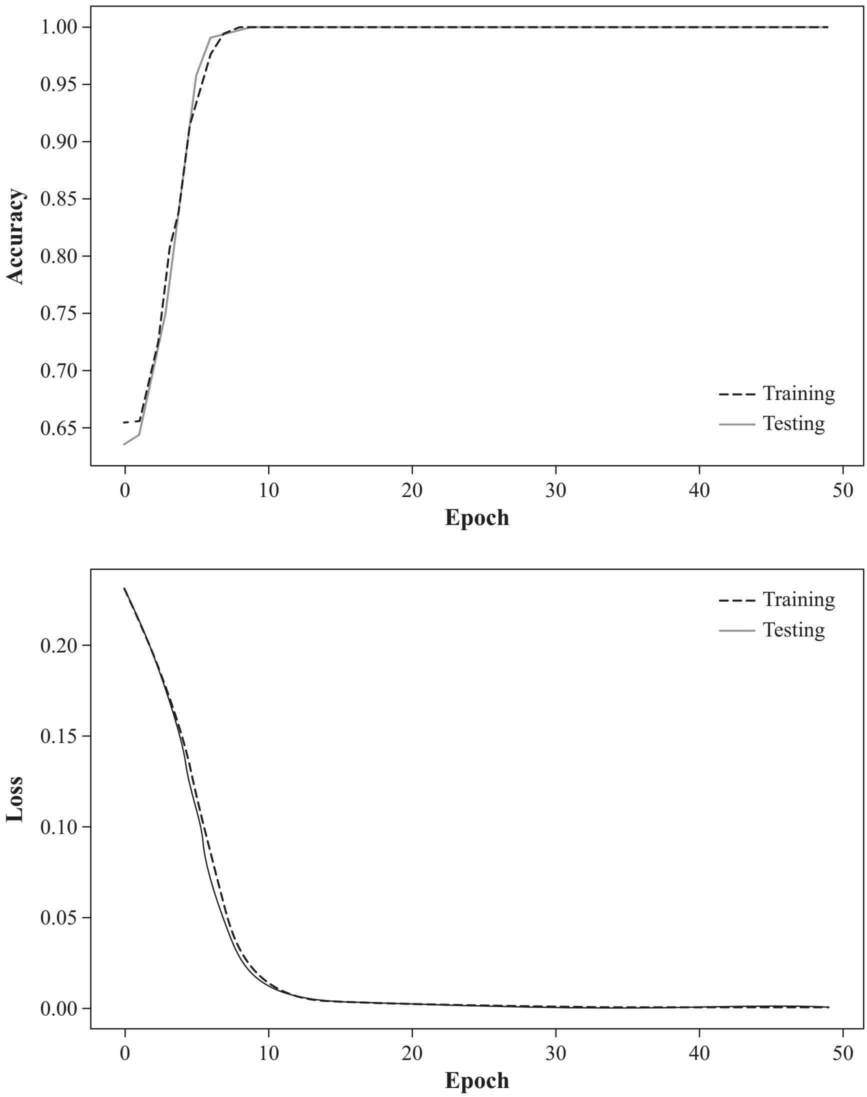

Figure 9.9 a) Training accuracy b) Training loss

the CbMM and 0.002% for CbFLNA, demonstrating a 2% enhancement over traditional approaches. Both methodologies exhibited high-performance capabilities in diabetes prediction. However, it's important to note that while these methods excelled in their predictive accuracy and performance, they lack security implementations. We intend to address this gap in future work by integrating robust security measures into these models. This enhancement is expected to yield even more promising results, ensuring the

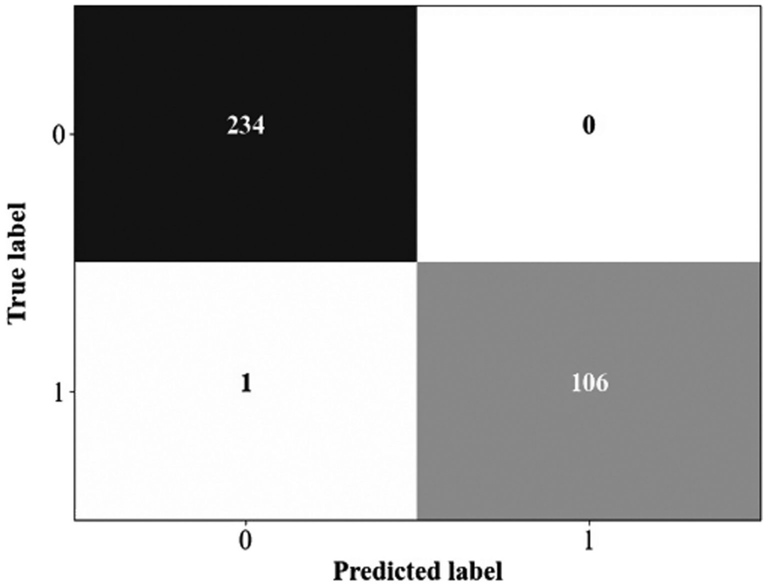

Figure 9.10 Confusion matrix

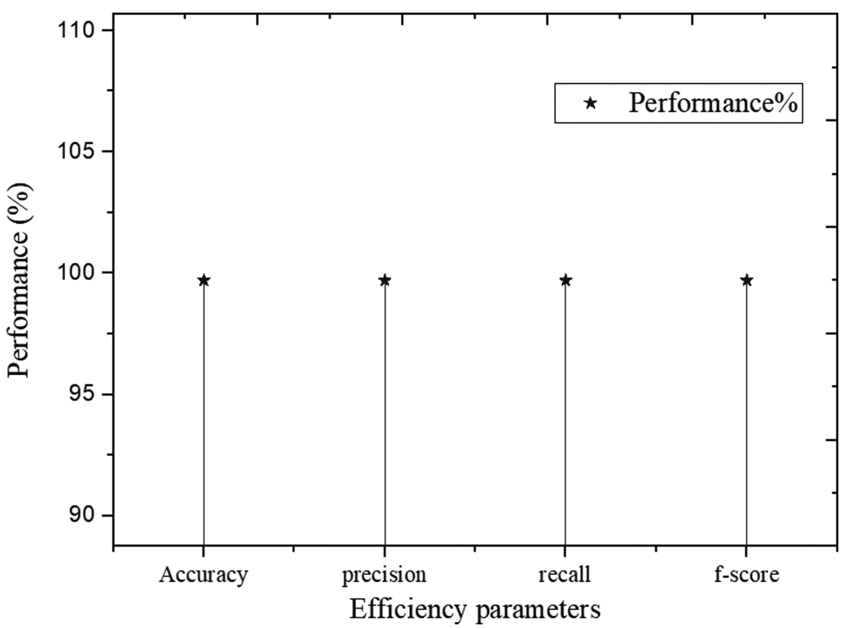

Figure 9.11 Performance of CbFLNA

precision and privacy of diabetes predictions for the benefit of patients and the broader medical community.

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Chapter 10

Diabalance ML

Enhancing diabetes detection performance through dataset balancing strategies

Hirak Mondal, Saima Siddika, Anindya Nag, and Anupam Kumar Bairagi

10.1 INTRODUCTION

Diabetes, known for its knack of causing mischief with glucose levels in the body, is a rather common medical condition. During the process of eating, particularly when consuming food that contains a significant amount of carbohydrates, our body breaks down the meal into glucose, a form of sugar, which is subsequently released into the bloodstream. Insulin, secreted by the pancreas, is an essential hormone for regulating blood glucose levels and facilitating cellular uptake of glucose for energy production. When glucose starts piling up in the bloodstream because the body is not making enough insulin, it leads to those pesky elevated blood sugar levels. Hyperglycemia, also known as high blood glucose levels, is a common occurrence in diabetes, a medical condition characterized by either insufficient insulin production or the body's resistance to insulin [1]. Although the exact cause of diabetes is still unknown, many experts believe that both environmental and genetic variables have a significant impact. Moreover, obesity and inadequate physical activity have a substantial impact. Owing to a dearth of knowledge or the nonexistence of symptoms, diabetes often goes undiagnosed. This form of exposure possesses the capacity to inflict damage on numerous organs and physiological systems. Unmanaged hyperglycemia can result in significant chronic health consequences, such as cardiovascular disease, cerebrovascular accident, renal failure, myocardial infarction, peripheral arterial disease, visual impairment, vascular injury, and neuropathy. Diabetes often manifests with symptoms such as muscle weakness, extreme thirst, itching, slow wound healing, and poor vision. Three primary diseases fall under the category of diabetes: Type 1 diabetes (T1D), Type 2 diabetes (T2D), and gestational diabetes [2]. The immune system mistakenly targets the insulin-producing pancreatic cells in T1D, an autoimmune disorder. While diabetes can strike at any age, it tends to make its debut in the younger crowd. The symptoms of T1D diabetes usually appear suddenly and might be severe. Typical symptoms of T1D comprise frequent urine (polyuria), heightened thirst (polydipsia), heightened

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hunger (polyphagia), weight loss, blurred vision, and exhaustion. Insulin resistance or insufficient insulin secretion causes abnormal glucose levels in the bloodstream, which is a hallmark of T2D. This issue is more common and often linked to lifestyle variables such as obesity and inadequate physical activity. T2D can occur at any age but is more frequently seen in adults. The symptoms of T2D usually appear gradually and may initially be mild. These symptoms are frequently associated with medical disorders such as obesity, hypertension, dyslipidemia, arteriosclerosis, and other diseases. Gestational diabetes is a transient illness that arises during pregnancy and usually resolves after childbirth [3]. However, women who have experienced gestational diabetes have an increased probability of getting T2D later on. Diabetes can lead to several severe complications, such as heart attack, amputation of the lower limbs, diabetic retinopathy, neuropathy, and other related disorders. These complexities contribute to elevated rates of morbidity and mortality.

The global data reveal that the total number of individuals who received a diagnosis of diabetes in the year 2010 was an astonishing 285 million. In 2012, it ranked as the fifth leading cause of death for women and the eighth leading cause of death for men. Global estimates for 2013 indicate that diabetes affected almost 382 million people [4]. The present projections indicate that by 2030, the figure will have increased to 552 million. Not only that, 6.4% of adults – or half of the population – are projected to go untreated. On top of that, 85% of the world's diabetics will reside in developing nations by 2030, according to estimates. According to the International Diabetes Federation (IDF), a staggering 783 million people, or roughly one in eight adults, will have been impacted by diabetes by 2045. This signifies a 46% surge in comparison to the existing prevalence. Therefore, the utilization of advanced diabetes detection techniques enables those who are at risk of the condition to take proactive measures to slow down its progression and improve their general health. Timely identification of diabetes can significantly reduce its severity and underlying risk factors. Enhancing accuracy in automated identification is essential for the prompt detection of diabetes. To minimize the effects of diabetes and improve the quality of patient care, substantial research has been conducted in different fields, including machine learning (ML). Supervised ML models are valuable tools for the detection and control of diabetes, a persistent medical condition [5]. ML models exhibit a high level of accuracy when it comes to predicting the diagnosis and progression of diabetes. These models depend on information about a patient's medical history, risk factors, and genetic makeup. ML-based systems can function as both feature selection strategies (FST) and classifiers [6]. Moreover, it assists persons in accurately identifying diabetes. However, the main challenge in accurately classifying the risk of diabetes rests in the work of determining the most efficient classifier. The probability of diabetes can be accurately predicted by training a machine learning classifier with a dataset. The following classifiers are utilized: random forest (RF), K-nearest

neighbors (KNNs), multilayer perceptron (MLP), support vector machines (SVMs), decision tree (DT), artificial neural networks (ANNs), naive Bayes (NB), logistic regression (LR), Gaussian naive Bayes (GNB), XGBoost (XGB), gradient boosting (GB), and LightGBM (LGM). Age, family history, body mass index (BMI), cholesterol, and blood glucose levels are the usual suspects when it comes to conventional risk assessment methods. While these measures have advantages, they may not completely capture the complex interplay of various risk factors that lead to the onset of diabetes. However, it is quite difficult to choose the most suitable method for prediction based on these features. Detecting unbalanced data is a substantial challenge in the profession. Obtaining balanced datasets in real-life scenarios is infrequent, and the class that lacks proper representation typically experiences a higher incidence of misdiagnosis.

The current research report delineates the subsequent pivotal measures to get enhanced precision.

- **Dataset Balancing:** We examined the problem of imbalanced datasets in the domain of diabetes detection. Imbalanced datasets, which have a significant difference in the occurrence frequency of distinct classes, can lead to biased models that favor the dominant class. We employed the Synthetic Minority Over-sampling Technique (SMOTE). This method improves the effectiveness of ML models by ensuring that both categories are adequately represented during the training phase. By applying the SMOTE to our dataset, we effectively created a balanced dataset that precisely reflects the distribution of classes. Consequently, our method for detecting diabetes gained enhanced accuracy and reliability.
- **Model Selection and Hyperparameter Tuning:** The choice of three ML models, namely SVM, LR, and GNB, was determined based on their suitability for diabetes detection. We conduct hyperparameter optimization to improve the system's performance. Furthermore, we fine-tuned parameters such as the kernel type, regularization parameter (C), and gamma for the SVM model. The hyperparameters, namely the regularization parameter (C) and the penalty type (L_1 or L_2), were fine-tuned for the logistic regression model. The GNB model was optimized for the smoothing parameter (alpha) due to its inherent simplicity.
- **Model Comparison and Performance Evaluation:** We evaluated the effectiveness of the model by utilizing criteria such as precision, recall, F1-score, and accuracy.

The following chapter is organized in the following manner: in Section 10.2, find a delightful compilation of the latest research on the matter. Section 10.3 presents a summary of the dataset, the proposed methodology, and the assessment metrics. Section 10.4 provides a thorough explanation

of the different experimental results and their accompanying explanations. The task is ultimately finalized in section 10.5.

10.2 LITERATURE REVIEW

Lots of researchers have employed ML approaches to extract knowledge from existing medical data in the field of diabetes research. Scientists have been conducting experiments using different ML methods to forecast diseases at the earliest possible stage. To improve the outcomes of the model, many ML methods, specifically hybrid techniques, have been created. This text will discuss some of the relevant literature in the field.

Alam et al. [1] employed a dataset consisting of 768 female participants and nine variables, which encompassed the medical history and blood test results of the patients. The authors utilized principal component analysis (PCA) to pick features and employed Association rule mining to uncover correlations between variables. This analysis indicated a robust association between diabetes and BMI and glucose levels. For diabetes prediction, three ML algorithms ANN, RF, and K-means clustering were employed. At 75.70 %, the ANN model was the most accurate, followed by the RF model at 74.70%, and the K-means clustering model at 73.40%.

To detect diabetes early, Dutta et al. [2] suggested an ensemble ML model. The researchers employed two separate datasets, specifically DDC-2011 and DDC-2017. The DDC-2011 dataset consists of 4751 instances of diabetes and 2814 instances of non-diabetes. The DDC-2017 dataset comprises a total of 3492 instances categorized as diabetes and 4073 instances categorized as non-diabetic. With DT, RF, XGB, and LGB making up the ensemble model, the best performance was obtained. Its AUC was 0.832, and its accuracy was 73.5%.

Bhat et al. [3] proposed a model that investigates the prevalence of diabetes and explores the use of ML for early diagnosis in the Bandipora district of North Kashmir. The study utilized a clinical dataset acquired from a physician in Bandipora, consisting of data from patients who underwent diabetes tests between April 2021 and February 2022. The study examined six ML approaches, including RF, MLP, SVM, DT, GB, and LR, to predict early-onset diabetes. When it came to diabetes prediction, the RF algorithm was the most accurate with a rate of 98%. MLP came in second with 90.99%, SVM with 92%, GBC with 97%, DT with 96%, and LR with 69%.

Maniruzzaman et al. [4] proposed a method that employed a dataset acquired from NHNES, encompassing 6561 participants, consisting of 657 individuals diagnosed with diabetes and 5904 individuals without diabetes. Five classifiers were employed: LR, NB, DT, AdaBoost, and RF. The performance was evaluated using three partition methods (k_2, k_5, and k_{10}) with several trials for each combination of model and approach. The LR-based

feature selection combined with the RF classifier achieved the highest overall performance, with an accuracy of 94.25% and an AUC of 0.95 for the k_{10} protocol.

Faruque et al. [5] introduced a model that relies on a dataset comprising numerous aspects or risk factors of diabetes mellitus. The dataset was collected from 200 patients at the MCC, Bangladesh. This study employed four commonly used ML techniques, namely SVM, NB, KNN, and C4.5 (DT). The results suggest that the C4.5 decision tree method fared better than other ML algorithms in properly forecasting diabetes mellitus, obtaining an accuracy rate of 73.5%.

Hasan et al. [7] did a study on the utilization of ensemble learning, a technique that combines many ML algorithms, to forecast diabetes. The researchers utilized the readily available Pima Indians Diabetes Dataset. K-fold cross-validation was employed in conjunction with many ML classifiers, including KNN, DT, RF, AdaBoost, XGB, NB, and MLP. Afterward, the individual classifiers were combined by using a weighted aggregation method. The weights were assigned according to the AUC of each model. This achieves a superior performance compared to the most advanced results, with an increase of 2.00% in terms of AUC.

Chollette et al. [8] developed a robust ML framework for building accurate and reliable prediction models for diabetes. The system uses Spearman correlation for selecting features and polynomial regression for imputing missing values. They propose several supervised ML models for categorization, including the RF model, the SVM, and their two-generative deep neural network (2GDNN) model. The proposed 2GDNN model provides high scores for precision, sensitivity, F1-score, train accuracy, and test accuracy, as demonstrated by the experiments that were carried out on the PIMA Indian and LMCH diabetic datasets. Specifically, using the PIMA Indian dataset, the model achieves scores of 97.34% for precision, 97.24% for sensitivity, 97.26% for F1-score, 99.01% for train accuracy, and 97.25% for test accuracy. Using the LMCH diabetes dataset, the model achieves scores of 97.28% for precision, 97.33% for sensitivity, 97.27% for F1-score, 99.57% for train accuracy, and 97.33% for test accuracy

Table 10.1 provides a comparative study of past research using the dataset, missing data imputation techniques, feature selection methods, classifiers, and performance parameters.

10.3 MATERIALS AND METHODOLOGY

Our proposed approach involves two key stages: data classification and preprocessing. We have come up with a clever way to determine whether or not a patient has diabetes by analyzing specific diagnostic measurements found in the dataset. To achieve the goal, our approach comprises multiple sequential stages. The stages involved in this procedure are as follows:

Table 10.1 Review of relevant literature summarized

Reference	*Year*	*Dataset*	*Classifier*	*Accuracy (%)*
[9]	2021	LMHC	XGB	87.60%
[10]	2021	PIDD	MLP	92.31%
[11]	2022	PIDD	KNN	82.00
			SVM	81.70
[12]	2020	PIDD	DT	95.00
[13]	2018	PIDD	NB	81.9 0
[14]	2018	Diabetes	RF	80.84
[15]	2018	PIDD	RF	92.26
[16]	2019	PIDD	SVM	76.00
			KNN	75.00
			RF	76.00
[17]	2022	Type-2 diabetes datasets	ANN	80.00
			RF	77.00
			DT	76.00

collecting a dataset on diabetes that includes the required patient attributes, preprocessing the numeric value attributes, applying various ML classification techniques, and doing predictive analysis on the gathered data. The following stages will be concisely analyzed:

10.3.1 Detailed description of the dataset

The diabetes dataset utilized in this study was obtained from Kaggle in order to assess the predictive capability of the ML model. The collection has 16 attributes and 390 records, with 85% denoting negative situations and 15% denoting positive examples. The aforementioned records provide data about the patients [18]. The sample comprised 58% female patients and 42% male patients. Table 10.2 offers a thorough summary of all features.

The dataset's attributes are presented in a histogram in Figure 10.1. The dataset includes a comprehensive collection of information for numerous parameters, including glucose, cholesterol, HDL cholesterol, height, weight, body mass index, systolic and diastolic blood pressure, waist and hip circumferences, and waist-to-hip ratio, among many others.

10.3.2 Data pre-processing

The processing of data is an essential step in the analysis of data and the creation of ML models. Real-world data frequently contains noisy, inconsistent data, or missing values. The first step is to clean up the data so it can be better analyzed or modeled. Data pre-processing is primarily focused on improving the quality of the data, making it easier to manipulate, and

Table 10.2 Description of the dataset

SL.	Attribute Name	Type	Mean ± Std. Deviation	Quantiles Min	25%	50%	75%	Max
01.	patient_number	Numeric	196 ± 113	1	98	196	293	390
02.	cholesterol	Numeric	207 ± 44.6	78	179	203	229	443
03.	glucose	Numeric	107 ± 53.7	48	81	90	108	385
04.	hdl_chol	Numeric	50.3 ± 17.3	12	38	46	59	120
05.	chol_hdl_ratio	Numeric	41.8 ± 20.6	2	31	41	53	193
06.	age	Numeric	46.8 ± 16.4	19	34	45	60	92
07.	gender	Nominal	-	-	-	-	-	-
08.	height	Numeric	66 ± 3.91	52	63	66	69	76
09.	weight	Numeric	177 ± 40.4	99	150	173	200	325
10.	bmi	Numeric	262 ± 102	16	227	274	318	558
11.	systolic_bp	Numeric	137 ± 22.8	90	122	136	148	250
12.	diastolic_bp	Numeric	83.3 ± 13.5	48	75	82	90	124
13.	waist	Numeric	37.9 ± 5.75	26	33	37	41	56
14.	hip	Numeric	43 ± 5.66	30	39	42	46	64
15.	waist_hip_ratio	Numeric	78.3 ± 27.3	1	81	86	93	114
16.	diabetes	Nominal	-	-	-	-	-	-

ensuring the correctness and reliability of any subsequent analysis or modeling results. Data pre-processing can be accomplished through many techniques. Data pre-processing includes the utilization of cleansing, integration, reduction, transformation, and discretization procedures to ready the data.

Regarding the dataset utilized in our research, there were no instances of missing values. We have transformed categorical data into numerical data by assigning the values of 0 and 1 to the categories 'male' and 'female' respectively, in the attribute 'gender'. In the 'diabetes' attribute, the values 'no diabetes' and 'diabetes' were transformed into numerical values of 0 and 1, respectively.

Figure 10.2 shows the diagrammatic illustration of our proposed framework.

10.3.3 Data smoothing

Data smoothing is a process used to eliminate outliers from a dataset while preserving important patterns or trends to make the patterns more noticeable. Data smoothing can be used to improve the visual clarity of data visualizations by suppressing noise, making it easier to identify trends and patterns [19]. It allows for preparation of data for further analyses like forecasting or modeling, where noise can interfere with accuracy. To obtain

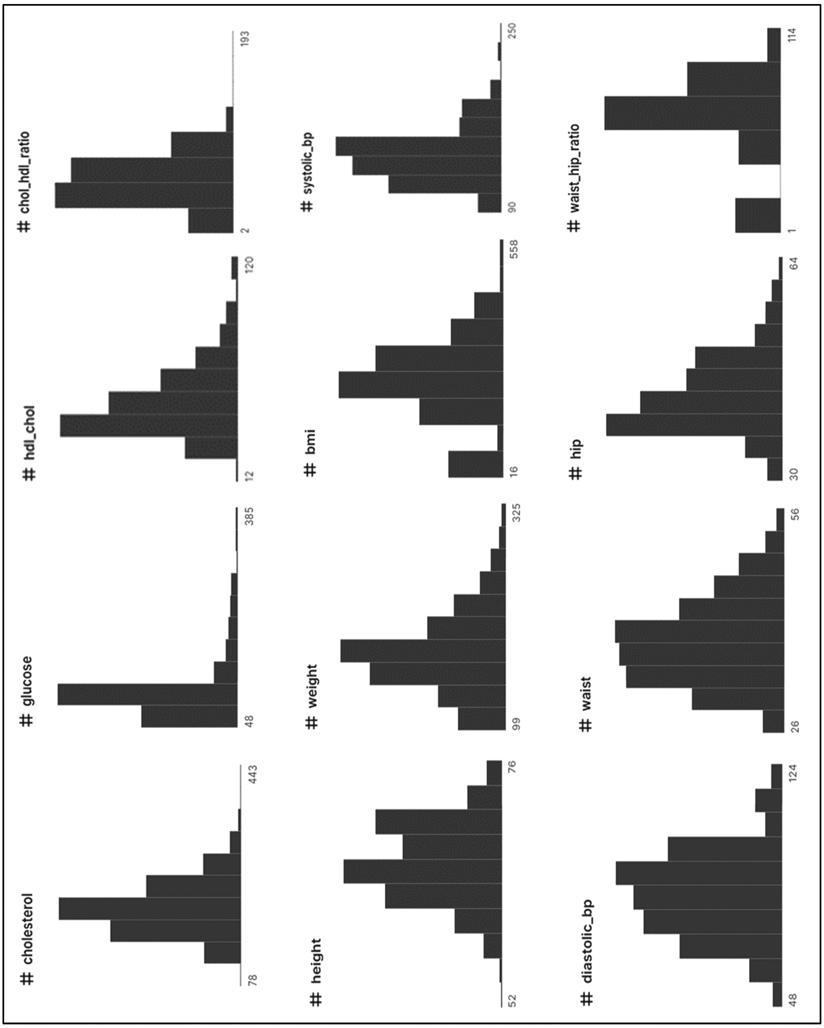


Figure 10.1 Histogram of each attribute

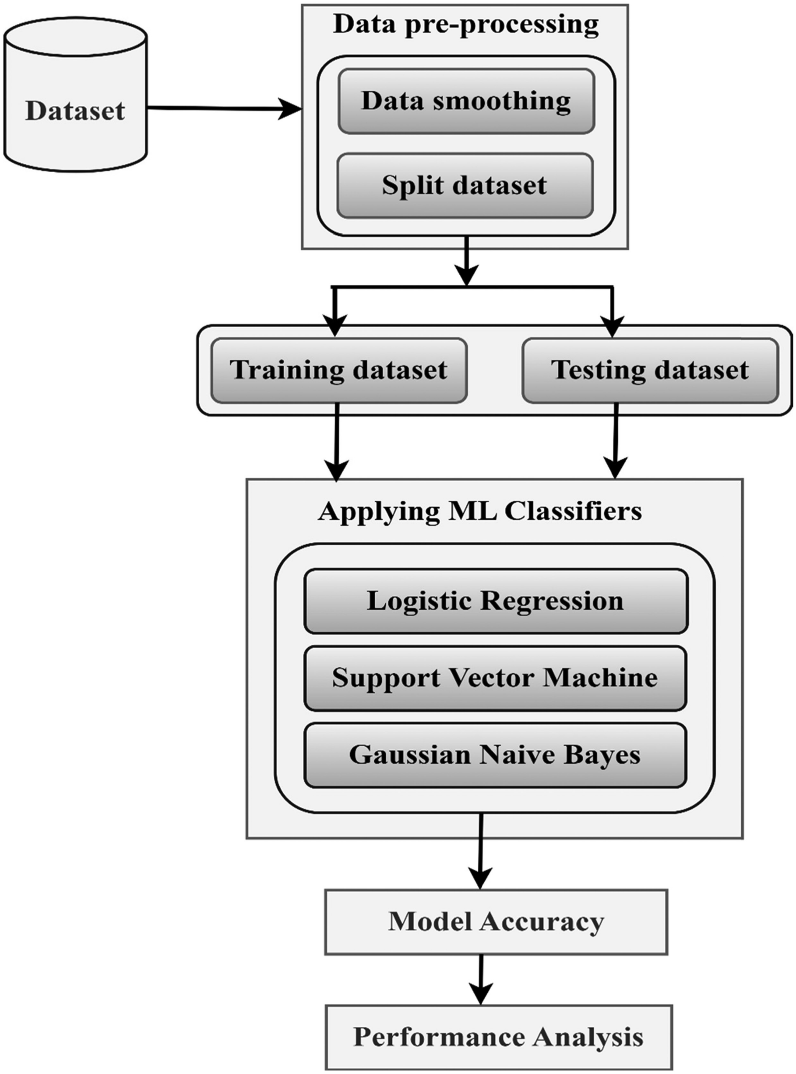


Figure 10.2 Proposed methodology for diabetes prediction

better accuracy, we performed a data smoothing technique on the dataset. Figure 10.3 illustrates the process of data smoothing.

10.3.4 Machine learning classifiers

After preparing the data for modeling, we employ three widely recognized ML classification algorithms, namely SVM, LR, and GNB, to forecast the

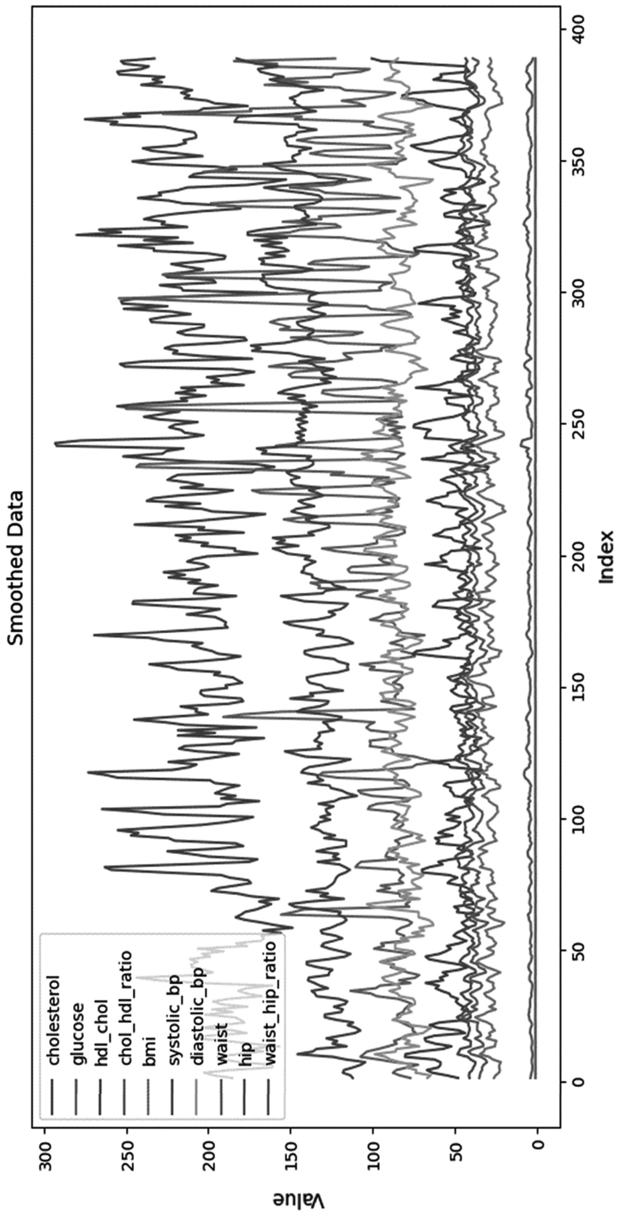


Figure 10.3 Data smoothing process

incidence of diabetes. Consequently, we offer a comprehensive summary of these techniques:

10.3.4.1 Support vector machines

SVMs are widely employed in ML for regression and classification purposes. In ML, it is most often used for categorization problems. Finding the optimal decision boundary that may effectively partition a multi-dimensional space into distinct classes is the main objective of the SVM approach. In the future, fresh data points can be accurately classified because of this. Using a hyperplane to create a clear distinction, the SVM method mathematically represents the data. Analyzing the issue space's dimensions defines the hyperplane. By spatially representing the training data as points, the SVM model facilitates comprehensive data separation for each category during data mapping. So, it uses the same space to map the updated data and makes a class prediction depending on where the values fall inside a range. In addition, SVM makes it easier to reduce data to guarantee that all data dimensions are equal. To get the marginal distance between classes, we use the support vectors and the vertices of each class to calculate the distance from the center of the hyperplane. SVM uses several parameters, such as C coefficients, intercepts, and kernels. The SVM technique relies heavily on kernels. Based on the properties of the received data, the kernels have been adjusted. Polynomial, linear, radial basis and quadratic kernel functions are the most common. The function can be utilized to categorize instance x' in the most efficient manner [20].

$$F(x') = \left[\beta_i c_i K(x_i, x') + b\right]$$
$$0 \leq \beta_j \leq C, \sum \beta_j p_j = 0, \beta_j \geq 0, j = 1, 2, \cdots, N, \tag{10.1}$$

The amount of the training examples is denoted by M. The class descriptor and the feature vector of the training instance are denoted by x_i and c_i, respectively. The bias is denoted by b. The class label c_i belongs to the set {1, -1}. The kernel function K (x_i, x') maps the input vectors to an enlarged feature space.

10.3.4.2 Logistic regression

LR is a statistical technique employed to categorize data into distinct classes. LR is a statistical model that categorizes its output into two classes: "yes" or "no", which are represented as 0 or 1, respectively. In this scenario, the presence or absence of diabetes in a patient is expressed by a binary representation of either 1 or 0. LR, despite its deceptive moniker, is a categorization methodology. It is utilized to ascertain the correlation between qualities and the likelihood of a particular outcome. The probability of an

instance belonging to the Diabetes class is denoted by p. Hence, the likelihood of an event being classified as part of the non-diabetes category can be mathematically represented as (1 – p). The relationship of log-odds with base b and model parameters β_i is written as:

$$log_b\left(\frac{p}{1-p}\right)=\beta_0+\beta_1 x_{i1}++\ldots+\ \beta_n x_{in} \tag{10.2}$$

A relationship between the response and one or more predictor variables can be established using LR by means of the probability logit function. LR and other ML algorithms are used quite a bit. The simplicity belies the fact that it is a potent weapon in a number of contexts. When doing regression analysis on a binary variable, linear regression is the way to go. One or more independent binary variables can have their relationships defined and made clear with the use of LR [21].

10.3.4.3 Gaussian naive Bayes

A probabilistic classification approach based on Bayes' theorem, GNB is an application of the naive Bayes algorithm. Classification issues with continuous input data are particularly well suited to its use. Just like previous iterations of naive Bayes, GNB takes the class label as a given and uses the assumption that the characteristics are conditionally independent. Each feature's mean and variance are calculated by the program. The method uses the estimated parameters to determine the likelihood of an instance belonging to each class in order to classify a new instance [22]. The GNB algorithm uses Bayes' theorem to calculate the posterior probability of each class, taking into account the input features.

$$P\left(y|x_1,x_2,\ldots,x_n\right)=\frac{p\left(y\right)\cdot p\left(x_1|y\right)\cdot P(x_2|y)\cdot\ldots\cdot P(x_n\mid y)}{p\left(x_1\right)\cdot p\left(x_2\right)\cdot\ldots\cdot p\left(x_n\right)}, \tag{10.3}$$

Where, $P\left(y|x_1,x_2,\ldots,x_n\right)$ is the posterior probability of class y given the input features. P (y) is the prior probability of class y. $P\left(x_1|y\right)$ is the likelihood of feature x_i given class y, which is assumed to follow a Gaussian distribution. $P\left(x_i\right)$ is the marginal probability of feature x_i.

10.3.5 Performance parameters

For measuring the performance of ML models, we employed different evaluation metrics such as precision, recall, and F-1 score and accuracy. The desired metrics are calculated using the confusion matrix. The confusion matrix consists of four components: true positive (TP), false positive (FP), true negative (TN), and false negative (FN) [22]. To ensure the effective and

efficient performance of an ML model, it is imperative to utilize a variety of evaluation metrics. This section offers a thorough discussion of various formulae used to compute performance metrics for ML models.

10.3.5.1 Accuracy

Accuracy is the most popular and often used evaluation metric in ML since it is simple and straightforward [23]. When a classifier shows a higher level of accuracy, it is usually considered better. The accuracy of an ML model can be calculated using the formula provided in equation 10.4.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{10.4}$$

10.3.5.2 Precision

The ability of an ML model to provide accurate predictions is quantified by its precision. The term "diabetic recall" refers to the percentage of people diagnosed with diabetes who are diagnosed with diabetes. By plugging the numbers into the formula in equation 10.5, we may find out how accurate an ML model is.

$$\text{Precision} = \frac{TP}{TP + FP}\ , \tag{10.5}$$

10.3.5.3 Recall

A classification model's recall, sometimes called sensitivity, is its capacity to accurately identify all relevant cases out of all the examples that belong to a given class. The computation determines what percentage of patients with diabetes was accurately predicted relative to the total number of patients with diabetes [24]. Formula 10.6 provides an equation that can be used to calculate the Recall of an ML model.

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{10.6}$$

10.3.5.4 F1-score

The F1-score offers a quantifiable assessment by calculating the weighted mean of accuracy and precision. Consequently, this score takes into account both cases of false positive and false negative [25]. To find an ML model's F1-score, use the formula in equation 10.7.

$$\text{F1} - \text{score} = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{10.7}$$

10.4 EXPERIMENT RESULT AND DISCUSSION

This section presents a comparative study of the outcomes from all ML models. A training dataset comprising 80% of the total was separated from a testing dataset comprising 20%.

10.4.1 Performance evaluation of the dataset

We employed a CSV format of the diabetes dataset, which was specifically tailored for use in ML. The patient either has diabetes or does not have diabetes. It is categorized into two separate groups. The collection includes a visual depiction of the quantity of individuals diagnosed with diabetes and those without diabetes. Figure 10.4 depicts the classification of the dataset into two distinct groups: individuals with diabetes and individuals.

Multiple factors influence an individual's vulnerability to diabetes, including glucose levels, systolic and diastolic blood pressure, BMI, and cholesterol. Unhealthy lifestyle choices greatly contribute to the onset of diabetes. Obesity and lack of physical exercise increase the levels of cholesterol in the bloodstream, which can lead to serious health problems. We graphed the data in Figure 10.5 to demonstrate the distribution of cholesterol levels in relation to the presence or absence of diabetes.

The patient's glucose level functions as a marker of their diabetic condition. Concentrations of glucose in the blood usually fall between the normal range of 70 mg/dL to 99 mg/dL. However, when the glucose level exceeds 126 mg/dl, it indicates the presence of diabetes. Behold, the illustrious Figure 10.6, showcasing the intricate dance of glucose levels within the patient's body.

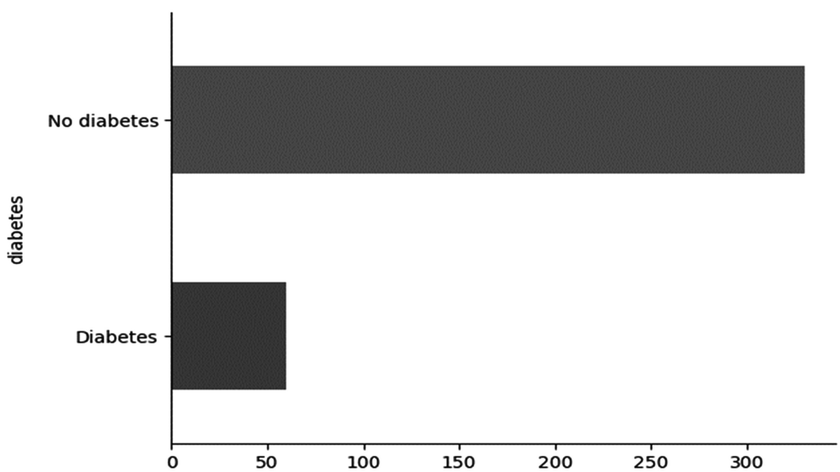


Figure 10.4 Separation of dataset according on whether subjects have diabetes or not

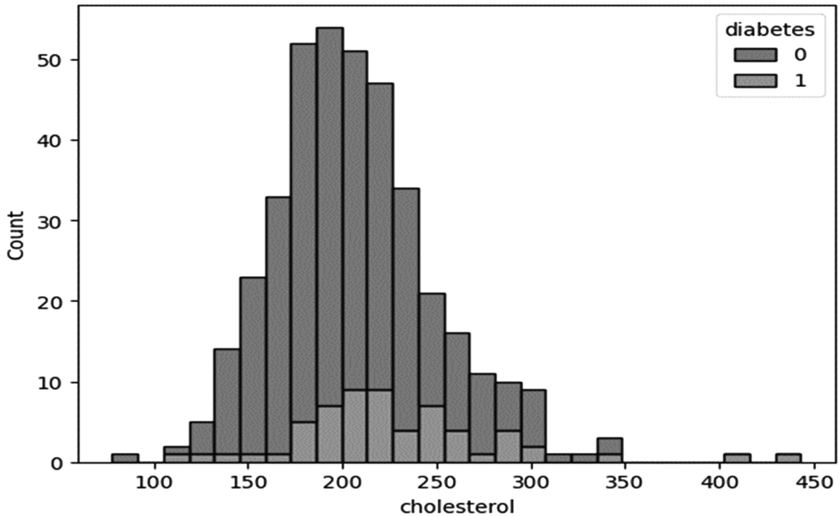


Figure 10.5 Distribution of cholesterol levels by diabetes status

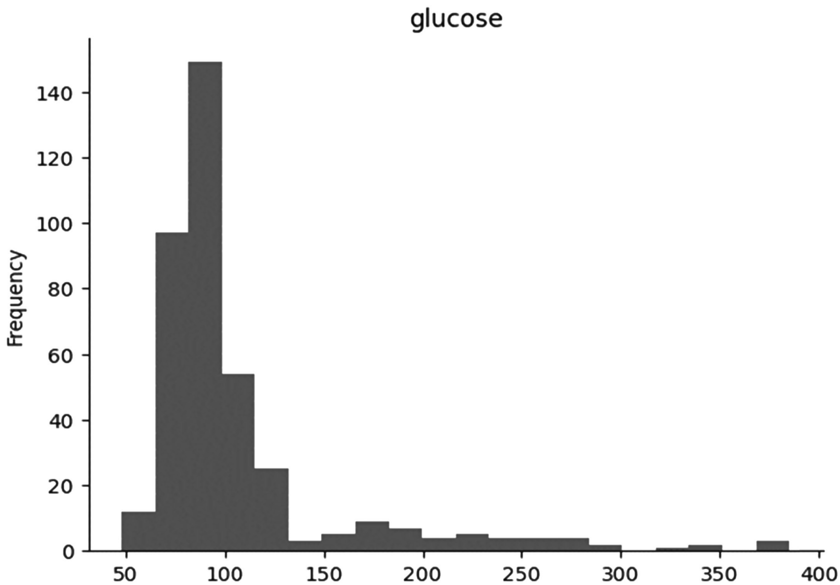


Figure 10.6 Glucose level in terms of frequency

10.4.2 Performance evaluation of ML classifiers

Three ML techniques were employed to examine the dataset in this study. The available approaches are SVM, LR, and GNB. Four measures were used to evaluate the effectiveness of the algorithms. We have showcased the

Table 10.3 Performance of the suggested ML classifier

Model	*Precision (%)*	*Recall (%)*	*F-1 score (%)*	*Accuracy (%)*
SVM	83.30	62.50	71.40	89.70
LR	76.50	81.25	78.80	91.00
GNB	66.70	87.50	75.70	88.50

results of our predictions in Table 10.3 to evaluate the performance of different ML algorithms.

After examining Table 10.3, it is evident that the logistic regression classifier exhibits greater performance in reliably predicting diabetes compared to other classifiers. As shown in Table 10.3, LR obtains the following results when applied to this dataset: precision of 76.50%, recall of 81.25%, and F-1 score of 78.1%, and accuracy of 91%. The outcomes demonstrate that LR exhibits superior performance compared to alternative learning strategies. The SVM and GNB classifiers achieved accuracy rates of 89.7% and 88.5% respectively.

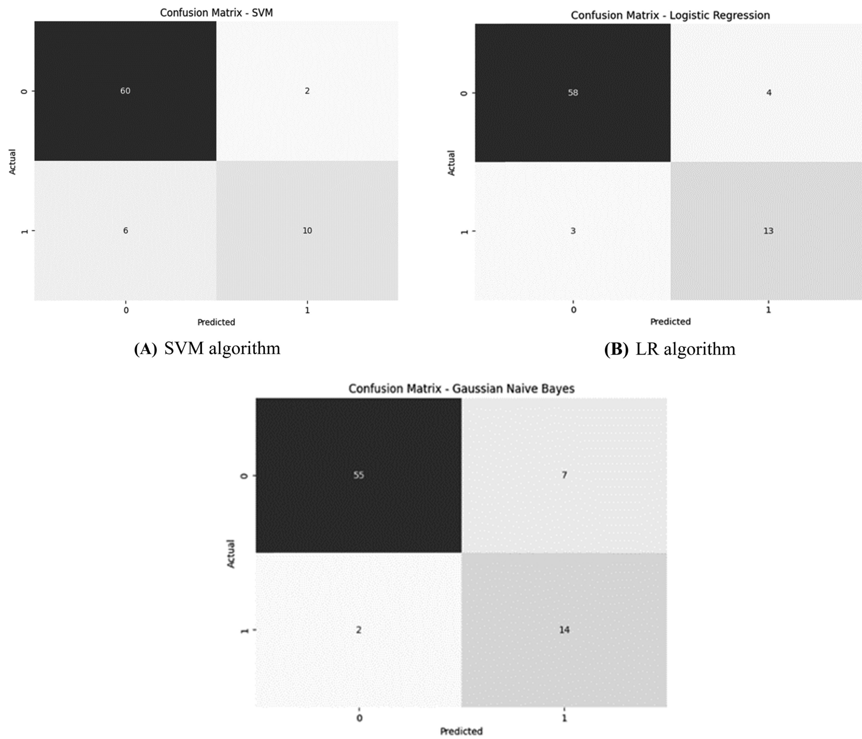
Statistical measures like F-measure, recall, specificity, and precision were applied to the confusion matrices in order to assess different ML methods. The data is organized in a tabular format, with the rows representing observed values and the columns representing anticipated values. The confusion matrices of the classifiers are displayed in Figure 10.7.

10.4.3 Comparison with previous research

Other researchers utilized various approaches to classify diabetes and achieved high levels of accuracy. To ascertain the efficacy of the algorithms, further performance metrics are necessary. We performed an additional comparative analysis between the ideal model produced in this experiment, logistic regression, and the superior model from a previous study conducted by numerous researchers. Table 10.4 presents the comparative results of several approaches.

10.5 CONCLUSION

This chapter employed ML methodologies to identify the timely detection of diabetes by considering multiple risk variables linked with the condition. ML algorithms are extremely important in the field of disease diagnosis. Early prediction of diabetes is crucial for determining the most suitable treatment approach for the patient. We utilized several established categorization techniques to diagnose diabetic patients in the medical field, and we evaluated their accuracy. An issue of classification has been identified in the correctness of the expressions. In order to accurately forecast diabetes,



(A) SVM algorithm

(B) LR algorithm

(**C)** GNB algorithm

Figure 10.7 Confusion matrices of all applied ML algorithms

Table 10.4 Comparative analysis

Ref.	*Year*	*Classifiers*	*Best Performed Classifier*	*Accuracy (%)*
[1]	2019	ANN, RF	ANN	75.70
[14]	2018	DT, NN, RF	RF	80.84
[25]	2018	SVM-linear, RBF, kernel SVM, ANN, KNN,	SVM-linear	89.00
[26]	2021	DT, RF, NB, NN, KNN, LR, SVM, AB	NN	88.60
[27]	2023	K-NN, BNB, DT, LR, SVM	K-NN	79.60
Proposed Method	**2024**	**SVM, LR, GNB**	**LR**	**91.00**

we conducted experiments utilizing three widely-used ML methods: SVM, LR, and GNB. These algorithms were trained and verified using a separate test dataset. Our model implementations have demonstrated that LR surpasses the other models in performance. The amount and nature of the

dataset, as well as the events themselves, impose constraints on the research. Furthermore, a structured dataset has been chosen, with the possibility of incorporating unstructured data in the future. Additional factors such as a familial history of diabetes, lack of physical activity, number of pregnancies, and smoking habits are intended to be taken into account in the future for the diagnosis of diabetes.

DATA AVAILABILITY STATEMENT

From Kaggle, the diabetes dataset was obtained.

https://www.kaggle.com/datasets/houcembenmansour/predict-diabetes-based-on-diagnostic-measures.

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Chapter 11

Identification of earthquake patterns for predictive modeling using decision tree classifiers to maintain sustainability

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11.1 INTRODUCTION

One of the most damaging and unexpected natural disasters in the world, earthquakes seriously harm people's lives, property, and infrastructure. Even while scientists are getting better at forecasting earthquakes, there are still a lot of unanswered questions regarding their frequency, location, and magnitude. The objective of this chapter is to form a machine learning model that can reliably and accurately forecast earthquake severity based on a variety of input variables, such as geographic location, seismic activity, and past earthquake data. For this, it will make use of a variety of ensemble approaches and test the model's performance using cross-validation. The chapter's goal is to create a highly accurate and dependable model that can be used to enhance earthquake preparedness and response operations in seismically active areas by utilizing ensemble techniques and cross-validation [1].

The overall goal of this research is to create a highly accurate and dependable earthquake prediction model by applying cutting edge machine learning techniques. By doing this, it seeks to advance our knowledge of these intricate natural phenomena, ultimately aid in the preservation of human life, and lessen the harm that earthquakes can inflict. Since these plates are always moving, earthquakes may result from their interactions near plate borders. The accumulated energy from two tectonic plates grinding against one another, becoming stuck, or experiencing stress finally releases seismic waves, which cause the earth to tremble.

The point on Earth's surface that is directly above the epicenter of an earthquake is known as the epicenter. The earthquakes magnitude varies, ranging from minor tremors that could go unreported to powerful events that can result in substantial damage and fatalities. An earthquake's size is determined by its magnitude, with higher magnitudes denoting more potent tremors. Earthquake magnitudes are frequently expressed using the Richter scale and the moment magnitude scale. Numerous secondary impacts, including landslides, tsunamis, and ground ruptures, can be caused by

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earthquakes. They are a global occurrence and a natural and dynamic aspect of Earth's geological processes. Seismologists research earthquakes to learn more about their origins, features, and possible threats to human populations. The tectonic plates of the Earth shift, causing earthquakes. Earthquakes may result from the interactions at these plates' borders.

The primary causes of earthquakes are as follows:

Tectonic Plate Movements: The movement of tectonic plates is the most frequent source of earthquakes. The semi-fluid asthenosphere lies beneath the several large and small tectonic plates that make up the Earth's lithosphere, or outermost layer. These plates can slide past one another (transform borders), move apart (divergent boundaries), or collide (convergent boundaries) as they interact. An earthquake may eventually result from the tension and strain that these plate boundaries generate as a result of their movement when the stored energy is abruptly released.

Volcanic Activity: Earthquakes can also be caused by volcanic activity. Earthquakes and cracks can occur as a result of pressure from magma moving beneath the surface of the Earth. Seismic activity can also be produced by the collapse of volcanic structures or the violent eruption of volcanoes. Human Activities: Human activities that can cause or induce earthquakes include mining, geothermal energy extraction, reservoir-induced seismicity and hydraulic fracturing for oil and gas exploration. Seismic occurrences may result from these activities changing the stress distribution in the Earth's crust. Faulting: Movement has taken place along fissures known as faults in the crust of the Earth. Along these faults, earthquakes frequently happen when the built-up stress surpasses the rock's strength, breaking the rock and releasing energy. Seismic waves can be produced during an earthquake by the abrupt displacement along a fault [2].

The steady ascent of land masses that were previously supported by ice sheets during glacial times is known as isostatic rebound. There is a chance that earthquakes will occur as a result of the stress caused by the ice melting and the ground rebounding. Although it is impossible to stop earthquakes, humans can lessen their effects and lower the possibility that particular activities would cause an earthquake. The following actions can be taken.

Responsible Resource Extraction: In some geological contexts, mining and hydraulic fracturing (fracking) can cause seismic activity. Restrictions and policies that guarantee ethical resource exploitation can reduce the possibility of causing earthquakes. This could entail avoiding locations with known fault lines or seismic sensitivity, as well as monitoring and managing injection rates and pressures. Geothermal Energy Production: The process of extracting heat from the Earth's subsurface is known as geothermal energy extraction.

Even though it's usually seen as a clean energy source, there are situations where it might cause seismic activity. Induced seismic event risk can be reduced with careful geothermal reservoir monitoring and management. Reservoir management is another reason for the cause of earthquakes.

Because of the weight of the water and variations in the stress on the underlying rock, large reservoirs built by dams have the potential to cause seismic activity. Reservoir-induced seismicity can be reduced by using techniques like regulated reservoir filling and drawdown and close observation of nearby seismic activity.

Urban planning: Strict adherence to building norms and standards intended to withstand seismic forces is crucial when developing infrastructure in areas vulnerable to earthquakes. As part of this, it is imperative to guarantee that infrastructure such as buildings and bridges are engineered and built with earthquake resistance in mind. One such way to lessen the effects of earthquakes is to retrofit existing structures to increase their seismic resilience. The reduction of fatalities and property damage during seismic events can be achieved by educating the public about the risks of earthquakes and how to prepare for them. Community-level emergency response plans, earthquake exercises, and the promotion of safe building techniques are all examples of this. Research and Seismic Monitoring: Investing in research and seismic monitoring networks can help improve early warning systems and guide mitigation efforts by shedding light on earthquake processes and possible hazards. Monitoring seismic activity, ground deformation, and other possible earthquake activity indicators are all part of this.

These precautions can lessen the chance that human activity will cause an earthquake, which will lessen its effects on infrastructure and communities even though they cannot stop earthquakes from happening. Seismologists track seismic waves as they move through the interior of the Earth. These waves come from both artificial and natural sources, such as explosions caused by humans. Understanding the behavior of waves as they pass through various materials helps us understand the layers that comprise the Earth. Each earthquake's date of occurrence, location, depth, magnitude, number of casualties, and extra notes are listed in Table 11.1.

There are differences in the strength, depth, and impact of earthquakes. Seismic events can have a variety of effects anywhere from Ecuador to California, Indonesia to Japan. Some earthquakes have little effect on people, but others have terrible aftereffects that lead to extensive damage and fatalities.

The likelihood of earthquakes emphasizes how crucial it is to have robust infrastructure and be prepared in order to lessen their effects. In order to improve disaster response and reduce mortality in sensitive areas, research must continue and international collaboration is necessary.

This is because earthquakes are still unpredictable natural occurrences, even with improvements in monitoring and warning systems [3].

Based on a number of factors, including as their underlying causes, focal depth, and the ensuing geological motions, earthquakes can be categorized into numerous categories. These are a few typical kinds of earthquakes: The movement of tectonic plates along faults in the Earth's crust causes tectonic

Table 11.1 History of earthquake occurrence in 2023–2024 across the globe

Location	*Magnitude*	*Depth In (km)*	*Casualties*	*Date*	*Notes*
Canada	6.2	10	0	1/14/2023	Felt widely across state
Tokyo, Japan	5.8	8	3	2/20/2023	Buildings damaged
Chile	7.5	25	10	3/17/2023	Tsunami warning issued
Nepal	6.9	15	25	4/29/2023	Landslides reported
Indonesia	7.1	20	50	5/8/2023	Major infrastructure damage
Alaska, USA	6.5	12	2	6/12/2023	Minor damage to buildings
Greece	5.7	10	0	7/21/2023	Felt by local residents
New Zealand	6.8	18	15	8/5/2023	Aftershocks reported
Philippines	6.3	15	8	9/11/2023	Evacuations in affected areas
Turkey	7	22	20	10/19/2023	Significant structural damage
Iran	6.6	16	12	11/26/2023	Rescue operations ongoing
Mexico	7.2	30	30	12/15/2023	Tsunami alert issued
Fiji	6.4	14	5	1/2/2024	Minor damages reported
Japan	7.3	28	20	2/8/2024	Widespread power outages
Ecuador	6.7	20	10	3/18/2024	Communication disruptions

earthquakes, which are the most frequent type of earthquakes. Trenches related to plate tectonics can happen at divergent, transform, and convergent plate borders. Volcanic Earthquakes: Volcanic activity is responsible for the rock fractures caused by magma rising through the Earth's crust. Volcanic eruptions are frequently preceded or followed by them. The term "induced" refers to earthquakes that are brought on by human activity. Examples of these activities include mining, hydraulic fracturing (fracking), which is used to produce natural gas and oil, and reservoir-induced seismicity, which is brought on by enormous reservoirs filling behind dams. Earthquakes resulting from cave collapses or mine collapses: these earthquakes are frequently caused by mining activity or by groundwater dissolving rock.

Earthquakes resulting from explosive events, such as nuclear testing or massive chemical explosions, cause a quick release of energy. They are the outcome of the stretched rocks in the Earth's crust readjusting to the main shock. The sample earthquake-related disaster is depicted in the following figures.

This chapter offers the following contributions:

1. Compiling a dataset from different sources.
2. Preparing the gathered information for use.
3. Using the dataset to create test and training sets.
4. Use performance metrics to assess the model.
5. Apply it to generate forecasts using fresh, unused data.

Table 11.2 Analysis on the existing approaches

Reference No.	*Title*	*Algorithm Used*	*Accuracy (%)*
[1]	Earthquake Prediction using Machine Learning Algorithm	Random Forest Boosting	83 76
[2]	Major earthquake event prediction using various machine learning algorithms	Random Forest	76.97
		KNN	75.53
		MLP	74.82
		SVM	72.66
		Ada Boost	74.82
		CART	70.5
		SVM	64
	A Novel Ensemble Earthquake Prediction	KNN	76
[3]	Method (EEPM) by Combining Parameters		
	and Precursors	BoostDecision TreeRandom ForestEEPM	74808288
[4]	Small Earthquakes Can Help Predict Large Earthquakes: A Machine Learning Perspective	Random Forest	74
[5]	A New Algorithm for Earthquake Prediction Using Machine Learning Methods	Custom algorithm	83.9
[6]	Analyzing the Performance of GPS Data for Earthquake Prediction	Statistical Machine Learning	60

Table 11.3 Dataset description

Title	*Magnitude*	*Cdi*	*Alert*	*Tsunami*	*Sig*
M 6.5 – 42 km W of Sola, Vanuatu	6.5	7	Green	0	657
M 6.5 - 43 km S of IntipucÃ¡, El Salvador	6.5	8	Yellow	0	775
M 6.6 – 25 km ESE of LoncopuÃ, Argentina	6.6	7	Green	0	899
M 7.2 – 98 km S of Sand Point, Alaska	7.2	6	Green	1	860
M 7.3 – Alaska Peninsula	7.3	0	Green	1	820

Table 11.4 Contrasting accuracy with numerous models

Name of the Model	*Accuracy (%)*
DTC	92.1875
CVK	83.50
SVM	83.33
ET	82.8
LR	82.29
GNB	82.77

The chapter is organized as follows: Section 11.2 presents relevant work. A Section 11.3 provides a comprehensive plan or outline that outlines the techniques and procedures a researcher plans to use to carry out their study or research project on earthquakes. Section 11.4 deals with results and discussion. In the Discussion section, which comes after the Results section, we interpret and discuss the significance of the results by contrasting various models, such as random forest, decision tree, logistic regression, and others. Section 11.5 (Conclusion) summarizes the main ideas covered in the study and offers a succinct and understandable assessment of the general conclusions and their implications [4].

11.2 RELEVANT WORK

Pratiksha Bangar's article [1] "Earthquake Prediction Using Machine Learning Algorithms" offers a creative solution to the problems related to earthquake forecasting. The proposal seeks to improve the precision and dependability of earthquake prediction models by utilizing machine learning algorithms, which are very skilled in recognizing patterns and forecasting outcomes from intricate datasets. By offering advanced warning systems, this strategy has a great deal of potential to help communities and authorities take preventative action to lessen the effects of seismic disasters. But putting such a system into place calls for careful data gathering, strong algorithm development, and validation against past earthquake data. To fully realize this novel approach's potential and enhance earthquake readiness worldwide, cooperation among scientists, engineers, and policymakers is vital. The results are as follows, Accuracy with 83% for random forest, Prediction using boosting with 76%.

Roxane Mallouhy's article [2] "Major Earthquake Event Prediction Using Various Machine Learning Algorithms." It proposes an all-encompassing method for predicting major seismic events through the use of many machine learning algorithms. In order to create predictive models that can recognize patterns connected to significant earthquakes, Mallouhy's plan probably entails collecting a large amount of seismic data from many

sources, such as seismographs, satellite imaging, and geological studies. Additionally, Mallouhy's proposal probably highlights how crucial it is to continuously update prediction models and monitor seismic patterns in order to adjust to changing seismic patterns and increase forecasting accuracy over time. Mallouhy's research has the potential to dramatically advance our understanding of earthquake prediction and improve disaster preparedness efforts worldwide by utilizing cutting-edge machine learning techniques and interdisciplinary collaboration. Respected results are in terms of accuracy, Random Forest does better with 76.97% , which is quite similar to KNN's 75.53% and MLP and SVM's 74.82%.AdaBoost, MLP, and SVM all perform between 72.66% and 74.82%, although the CART model was predicted to perform at 70.5%.

Sumita Mukherjee's article [3] "A Novel Ensemble Earthquake Prediction Method (EEPM)" by combining parameters and precursors offers a novel method of earthquake prediction that combines a number of elements and factors. Predictive models using various datasets – each having distinct kinds of seismic data, geological details, and precursor signals linked to earthquake events – are probably going to be developed as part of the plan. Global earthquake monitoring networks' seismic records, geological surveys' data on fault lines and tectonic activity, satellite imagery's images of surface deformations, and environmental data measuring variations in groundwater levels, electromagnetic fields, or radon gas emissions are a few examples of the datasets that Mukherjee's research may have taken from. In order to assess the accuracy of the results and to ascertain whether the ensemble approach produces better results than the individual method, the EEPM and the aforementioned significant measures on various individual approaches that are produced using regression are compared in this work. SVM's performance measures have a value of 64%, KNN's is 76% Boost's is 74%, decision trees' is 80%, random forests' is 82%, and maximum-performing EEPM's is 88% [5].

Xi Wang's article [4] "Small Earthquakes Can Help Predict Large Earthquakes: A Machine Learning Perspective" offers a novel method of earthquake prediction. The plan most likely focuses on improving the accuracy of significant seismic event predictions by using data from both small and large earthquakes. Seismic data from a variety of sources, such as regional seismograph stations, worldwide earthquake monitoring networks, and geological surveys, may be included in Wang's research dataset. Together with additional elements including precursor signals, geological features, and environmental conditions, this dataset would include data on earthquake magnitudes, depths, locations, and timestamps. Results end up with Random Forest with an Accuracy of 74 % in 5.5 magnitude.

Nada Badr Jarah's article [5] "A New Algorithm for Earthquake Prediction Using Machine Learning Methods" presents a novel method of predicting earthquakes by utilizing machine learning concepts. The plan most likely calls for creating a brand-new algorithm made expressly to

examine seismic data and spot trends that point to seismic activity that could soon occur. The dataset Jarah employed for his study includes a wide variety of seismic records gathered from seismograph stations, geological surveys, and international earthquake monitoring networks. Data on earthquake magnitudes, depths, locations, and timestamps would be included in this dataset, along with other elements including precursor signals, geological traits, and environmental influences. The dataset analysis in Jarah's suggested approach is probably going to involve a combination of supervised, unsupervised, and semi-supervised machine learning techniques and its accuracy finally ends up with 83.9%.

Valeri Gitis' article [6] "Analyzing the Performance of GPS Data for Earthquake Prediction," by concentrating on the examination of GPS data, he makes a substantial contribution to earthquake prediction methodology. The plan most likely entails using GPS information to look into the connection between crustal changes and seismic activity. These datasets can be gathered from a variety of sources, including satellites, ground-based receivers, and global positioning systems. In order to examine the GPS data and find trends or abnormalities connected to earthquake precursors, Gitis study is probably going to make use of statistical and machine learning methods. The time-series data containing measurements of ground displacement, velocity, and acceleration taken by GPS sensors placed throughout earthquake-prone areas may make up the dataset used in Gitis's research. Researchers would be able to track minute variations in the Earth's crust that occur before seismic events thanks to this dataset, which spans a large geographic and temporal range. Periodic fluctuations or trends in the data that may indicate impending earthquakes can be found using time-series analysis techniques like Fourier analysis and autoregressive integrated moving average (ARIMA) models and 60% at its accuracy level.

11.3 PROPOSED METHODOLOGY

Because of its special qualities and skills suited to the intricacies of seismic data analysis, decision tree classifiers present a convincing method for forecasting earthquakes. Decision trees are very useful because they are interpretable, which is important when trying to figure out the complex dynamics that underlie seismic activity. By recursively dividing the feature space according to basic criteria, decision trees simulate human decision-making processes and produce an understandable and visible model structure. This interpretability helps researchers and stakeholders understand the mechanisms and contributing elements that drive seismic events, which helps with risk assessment and well-informed decision-making in the context of earthquake prediction.

Moreover, decision trees are well suited to manage the nonlinear correlations included in seismic information. Numerous geophysical factors, many

of which have complicated and nonlinear connections, might affect the likelihood of earthquakes. By segmenting the feature space into segments that are characterized by various seismic event outcomes, decision trees are particularly effective at capturing these nonlinear correlations. Because of their adaptability, decision tree classifiers can accurately represent the complex interrelationships between geological, geophysical, and environmental variables, offering a thorough understanding of the variables influencing the occurrence of earthquakes [6].

The capacity of decision tree classifiers to handle multiple data types, which are frequently seen in datasets for earthquake prediction, is another benefit. Seismic data may include a wide variety of data types, including categorical variables that reflect fault types and geological features and continuous variables like seismic wave amplitudes and depths. Decision trees simplify data analysis and make it easier to integrate various geophysical data types into earthquake prediction models because they can handle mixed data types with ease and don't require complicated preparation processes.

11.3.1 Architecture

To sum up, decision tree classifiers, by virtue of their interpretability, robustness to mixed data types, ability to handle nonlinear relationships, feature selection processes, and compatibility with ensemble learning approaches, offer a powerful and versatile solution for forecasting earthquakes. Using these advantages, decision tree classifiers offer a useful framework for evaluating seismic data and creating efficient earthquake prediction models that enhance efforts to reduce risk and prepare for disasters. To maximize the model's performance, cross-validation approaches were used to fine-tune its hyper parameters. To avoid overfitting, the model was then assessed using the validation set. Lastly, the independent testing set was used to assess the model's generalization capabilities.

11.3.1.1 Dataset used

The data being used includes numerical as well as categorical data which is stored in a csv. The dataset contains records of 782 earthquakes from 1/1/2001 to 1/1/2023. The meaning of all columns is as follows: title: the name assigned to the seismic event, magnitude: Date_time: Date and time, cdi: Earthquake magnitude In terms of the event range, the maximum reported intensity, mmi: Alert: The event's greatest estimated instrumental intensity The warning level is "green," "yellow," "orange," and "red." For tsunamis, it is "1" for incidents that occur in oceanic zones and "0" elsewhere. sig: a figure that expresses the event's significance. The greater the number, the more important the occasion.

Numerous parameters, including magnitude, maximum MMI, felt reports, projected effects, and network dependability (contributor's ID), are taken into account when grading an earthquake. Location accuracy is aided by parameters such as gap (azimuthal gap), dmin (closest station distance), and nst (total seismic stations used). mag The magnitude calculation method is determined by type. Depth is the depth at which seismic waves begin to form. Location coordinates are specified by latitude and longitude. The continent, the nation, and the location of the event inside the country are further details [11].

11.3.1.2 Data preprocessing

Before raw Earthquake data can be used for analysis and modeling, it must first be cleaned, formatted, and arranged. This process is known as information preparation in Earthquake. Numerical models, Categorical models and other data obtained from many sources are major sources of information for it. But this data could be collected irregularly, arrive in a variety of formats, and have mistaken or missing numbers. By addressing these issues, information preparation makes sure the data is ready for additional analysis and predictions [7].

In order to predict earthquakes, preprocessing stages entail getting both numerical and categorical datasets ready for examination. An overview of the preprocessing procedures is provided below:

Data Purification: Delete or imputation missing values: Determine whether to delete or impute missing values with acceptable values (e.g., mean, median, mode for numerical data, and mode for categorical data) after identifying them in both numerical and categorical data. Identifying and handling outliers: Use statistical techniques (such as Z-score and IQR) to identify outliers in numerical features and determine whether to eliminate, cap, or transform them [16].

Engineering Features: Make fresh features: Identify novel elements that could be helpful in the prediction of earthquakes. One possible approach would be to compute the separation between every data point and recognized fault lines. Converting variables of a category. Quantitatively express categorical variables using techniques such as label encoding or one-hot encoding.

Standardization and Normalization: Numerical features can be standardized or normalized to bring them to a common scale. This can help some machine learning algorithms work better. Normalization (scaling features to a range) or standardization (converting features to a mean of 0 and a standard deviation of 1) may be required, depending on the algorithm you're employing.

Managing Unbalanced Information: In case the dataset is unbalanced, meaning that one class is considerably greater than the other, employ

methods such as oversampling, under sampling, or creating synthetic data to achieve class balance.

The collection of the data is prepared for use in earthquake prediction models, such as machine learning algorithms, statistical models when these preprocessing stages are finished. In order for the prediction models to generate accurate and dependable predictions that are critical safety for the public and making the decisions across a range of industries, including emergency response, transportation, and agriculture—proper information preprocessing is required [12].

11.3.1.3 Training set

The training set is essential for creating and refining prediction models. The earthquake prediction model is taught or trained using a subset of historical data called the training set. In essence, the model "learns" from this historical data by spotting relationships, patterns, and trends that can be utilized to forecast the weather in the future. In this case, 80% of the dataset is regarded as the training dataset.

11.3.1.4 Testing set

It involves using the testing set to evaluate a prediction model's accuracy and performance after it has been trained using the training set. The testing set is a subset of past weather data that the model did not see during training. It serves as an independent dataset to assess how well the model can generalize its predictions to fresh, untested data. The testing dataset in this instance is 20% of the whole dataset.

11.3.1.5 Decision tree classifier – proposed model

Machine learning is an essential step in maintaining accuracy and creating higher expectations for the information provided. To move on with additional study and display the best accuracy figures with the lowest loss percentage, the "Decision Tree Classifier" model is suggested [15].

11.3.1.6 Model evaluation

The process of evaluating predictive models for earthquake prediction includes determining how well they anticipate seismic events. Measures such as precision, accuracy, F1-Score and recall are frequently employed to assess how well the model detects earthquakes while reducing false alarms. Furthermore, methods such as cross-validation contribute to the model's generalization and robustness.

Algorithm for Decision Tree Classifier

Algorithm for Decision Tree Classifier

Data Splitting: Begin by dividing the whole dataset.

$$D = \{ x1, x2, x3 \ldots, xn \}$$

Select a feature that divides the data into the most meaningful groupings.

$$F = \text{argmax Information Gain}(f, D)$$

Creating Nodes: Based on the selected feature's values, create a node by splitting the dataset into smaller groups.

$$\text{Node }(F)$$

Repeating: Choose the next best feature to split on and repeat the process for each subgroup.

$$D1, D2, D3, \ldots Dk = \text{Split}(F, D)$$

When specific conditions are satisfied, such as reaching a maximum depth or having an excessive number of data points, stop splitting.

$$\text{Stop condition}(D)$$

Making predictions: Based on the majority class within each final subgroup, make a prediction for it.

$$\text{Prediction }(Di) = \text{Majority Class}(Di)$$

Building Tree: Recursively work through this procedure until all of the data is correctly categorized, creating a decision tree.

$$\text{Build Tree}(Di)$$

11.4 RESULTS AND DISCUSSION

The results of the forecast method is usually presented in the results section of the earthquake report. This contains the model-generated forecasts as well as the actual earthquake observations, which are used to gauge how accurate the prediction is. The results are then analyzed and their ramifications are examined in the discussion section. The value of improvement strategies, the accuracy of earthquake prophecies, their events, and many other topics are important to cover in the conversation. The particular

goals of the analysis, the type of Earthquake research, and the data at hand will all influence what is included in the results and discussion section. Furthermore, adding visual aids like charts, graphs, and maps can improve comprehension of the findings and assist illustrate the discussion.

By contrasting and putting several models into practice, accuracy is examined. Generally speaking, accuracy can be a widely utilized assessment statistic to gauge a classification model's effectiveness. It shows the percentage of accurately anticipated cases (or data points) in the dataset relative to the all number of cases. When the dataset is well balanced, or the classes are roughly equally represented, accuracy becomes even more valuable [13].

Terms used in performance metrics:

Real Positive (RP): The TP, sometimes referred to as recall is used to determine the percentage of true positives that are really identified.

When the model accurately predicts the negative class, the result is referred to as True Negative (TN).

An indicator of a test's accuracy is called False Positive (FP). The false positive rate is defined, technically, as the probability of mistakenly rejecting the null hypothesis.

Contrary Negative (FN): The probability that a true positive would be missed by the test is shown by this statistic, which is sometimes referred to as the miss rate [8].

Accuracy = (No. of Correct Predictions) / (Total No. of Predictions)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}} \tag{11.1}$$

The following results are acquired from Table 4's comparison of various models' accuracy: With the highest accuracy of 92.1875%, the model proposed is called the decision tree classifier (DTC). Its cross-validation results show that K-fold (CVK) is used at 83.50%, support vector machine (SVM) at 83.33%, ensemble techniques (ET) with different optimizers model at 82.8%, logistic regression (LR) at 82.29%, and Gaussian naive Bayes (GNB) at 82.77%.

Precision rates the accuracy of different models predictions that are meant to be positive. It is employed in the fields of statistics and machine learning. In relation to the total number of anticipated positive occurrences, it is a measure of the proportion of predicted positive cases that are actually genuine positives. The precision of a model indicates its capacity to prevent false positives. Stated differently, it quantifies the percentage of the model's positive predictions that come true.

$$Precision = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{11.2}$$

Table 11.5 illustrates the comparison between precision values and models. The model proposed so-called decision tree classifier (DTC) with the highest Precision of 91 % and then cross validation using K-fold (CVK) at 80.50%, support vector machine (SVM) at 82%, ensemble techniques (ET) with different optimizers model with 79.18%, logistic regression (LR) at 80.29%, least with Gaussian naive Bayes [GNB] at 72.77% [14].

Recall is a performance metric that is also utilized in the statistical community. Recall can also be called true positive, sensitivity, or hit rate. The below formula is used to measure recall in binary classification:

$$Recall = \frac{TP}{\mathrm{TP} + \mathrm{FN}} \tag{11.3}$$

Table 11.6 illustrates the comparison between recall values and models. The model proposed so-called decision tree classifier (DTC) with the highest Precision of 89.99 % and then cross validation using K-fold (CVK)at 81.10%, support vector machine (SVM) at 80.189%, ensemble techniques (ET) with different optimizers model with 79.18%, logistic regression (LR) at 70.12%, least with Gaussian naive Bayes [GNB] at 70.67% [9].

When dealing with binary classification problems, which have two classes: positive and negative, one performance measure that is frequently utilized is the F1-score. It offers a balanced assessment of a model's accuracy in relation to unbalanced class distributions since it symbolizes the

Table 11.5 Contrasting precision with numerous models

Name of the Model	*Precision (%)*
DTC	91
CVK	80.50
SVM	82
ET	79.18
LR	80.29
GNB	72.77

Table 11.6 Contrasting recall with numerous models

Name of the Model	*Recall (%)*
DTC	89.99
CVK	81.10
SVM	80.189
ET	79.18
LR	70.12
GNB	70.67

Table 11.7 Contrasting F1-score with numerous models

Name of the Model	*F1-Score (%)*
DTC	86
CVK	76.5
SVM	65.7
ET	63.88
LR	59.99
GNB	54.87

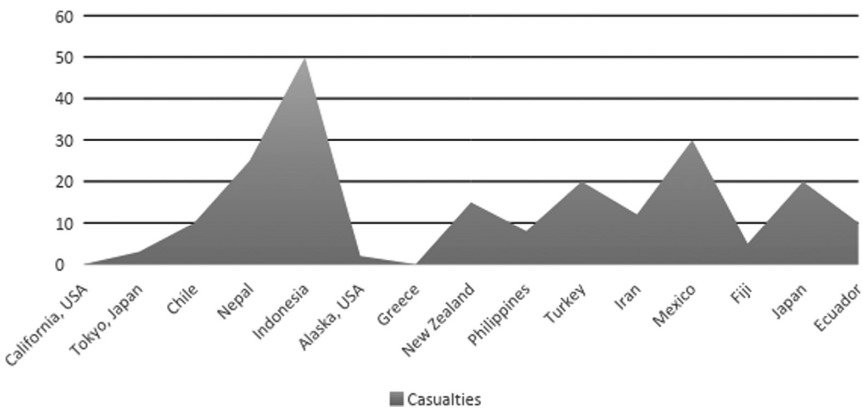

Figure 11.1 Representation of number of deaths with respect to locations graphically

harmonic mean of precision and recall. The formula below is used to determine the F1 score:

$$F1\,Score = \frac{2*(Precisoion*Recall)}{(Precisoion+Recall)} \tag{11.4}$$

Table 11.7 illustrates the comparison between F1-score values and models. The model proposed so-called decision tree classifier (DTC) with the highest F1-score of 86 % and then cross validation using K-fold (CVK) at 76.5%, support vector machine (SVM) at 65.7%, ensemble techniques (ET) with different optimizers model with 63.88%, logistic regression (LR) at 59.99%, least with Gaussian naive Bayes (GNB) at 54.87% [10].

11.5 CONCLUSION

Infrastructure, property, and human life are all severely damaged by earthquakes, which are among the world's most devastating and unpredictable

Figure 11.2 Collapsing the constructions

Figure 11.3 Destroyed city by earthquake

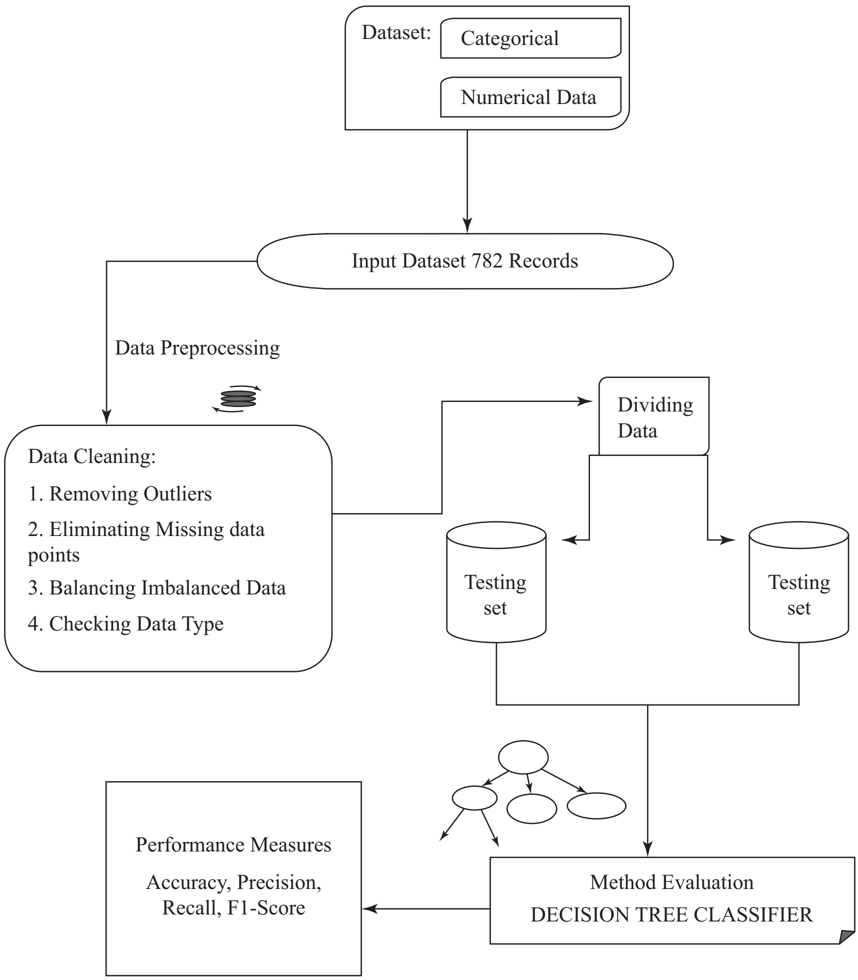

Figure 11.4 Decision tree classifier model for earthquake prediction

natural disasters. Even though scientists have come a long way in forecasting earthquakes, many aspects of these natural disasters remain unclear, such as their size, location, and timing. The aim of this chapter is to create a machine learning model that can reliably and accurately forecast earthquake severity based on different input variables, such as geographic location, seismic activity, and past earthquake data. For this, the work will make different ensemble approaches and test the model's performance using cross-validation. The main goal is to create a highly accurate and dependable model that can be used to enhance earthquake preparedness and response operations in seismically active areas by utilizing ensemble

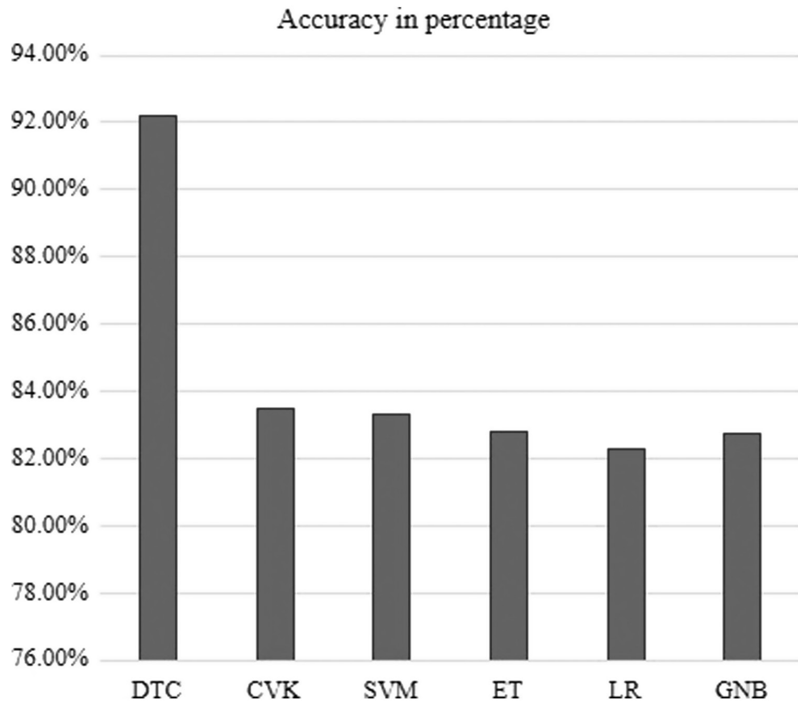

Figure 11.5 Contrasting accuracy with numerous models graphically

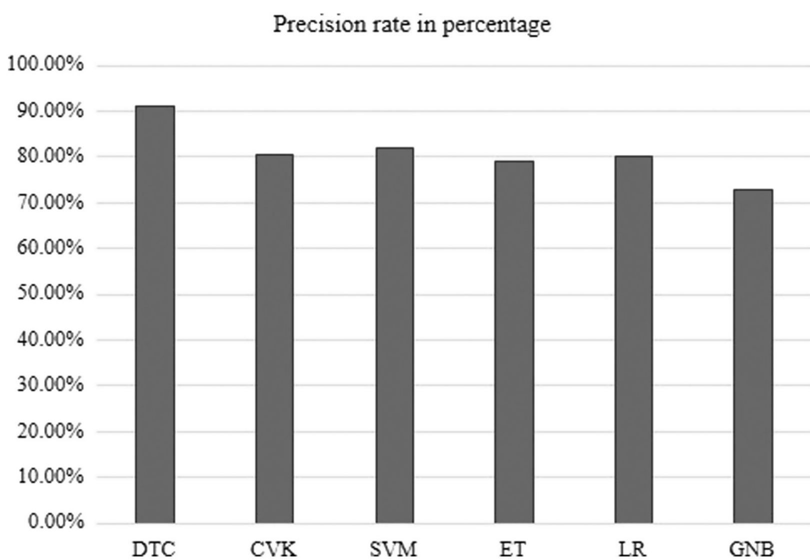

Figure 11.6 Contrasting precision with numerous models graphically

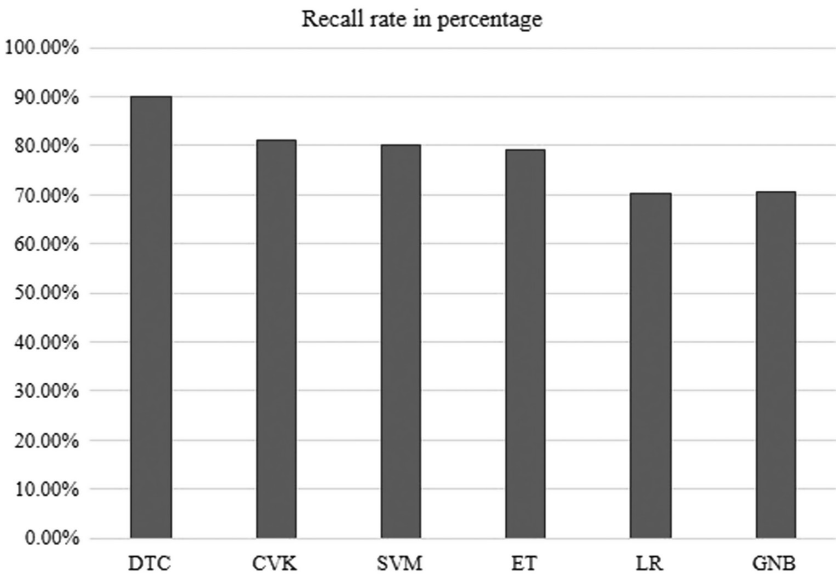

Figure 11.7 Contrasting recall with numerous models graphically

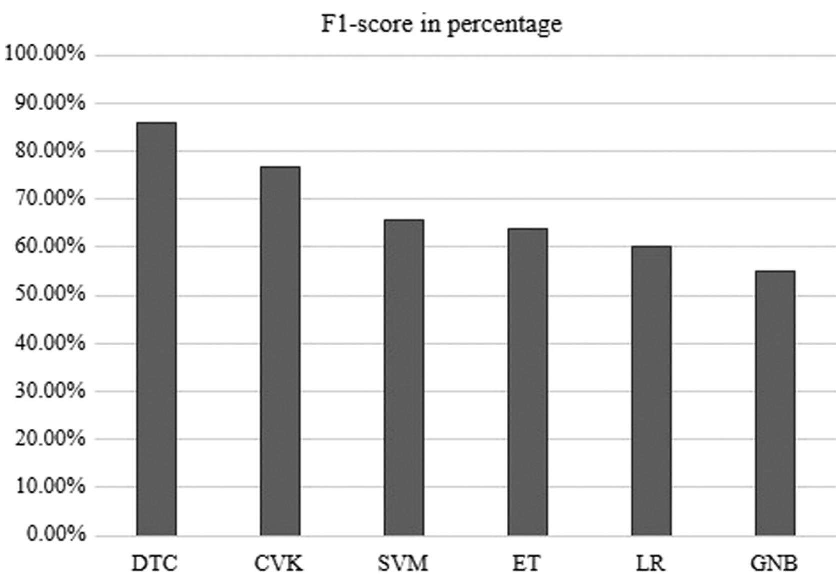

Figure 11.8 Contrasting F1-score with numerous models graphically

techniques and cross-validation. Overall, this chapter aims to use advanced machine learning techniques to develop a highly accurate and reliable model for earthquake prediction. By doing this, it seeks to advance our knowledge of these intricate natural phenomena, ultimately aiding in the preservation of human life and lessening the harm that earthquakes can inflict.

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Index